Laura Vartain Horn (SBN 258485)
KIRKLAND & ELLIS LLP
555 California Street, Suite 2700
San Francisco, CA 94104
Telephone: (415) 439-1625
laura.vartain@kirkland.com

Allison M. Brown (Admitted *Pro Hac Vice*)
KIRKLAND & ELLIS LLP
2005 Market Street, Suite 1000
Philadelphia, PA 19103
Telephone: (215) 268-5000
alli.brown@kirkland.com

Jessica Davidson (Admitted *Pro Hac Vice*)
KIRKLAND & ELLIS LLP
601 Lexington Avenue
New York, NY 10022
Telephone: (212) 446-4800
jessica.davidson@kirkland.com

Attorneys for Defendants
UBER TECHNOLOGIES, INC., RASIER, LLC,
And RASIER-CA, LLC

UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

SAN FRANCISCO DIVISION

IN RE: UBER TECHNOLOGIES, INC., PASSENGER SEXUAL ASSAULT LITIGATION This Document Relates to: ALL ACTIONS	Case No. 3:23-md-03084-CRB (LJC) **DECLARATION OF LAURA VARTAIN HORN IN SUPPORT OF DEFENDANTS UBER TECHNOLOGIES, INC., RASIER, LLC, AND RASIER-CA, LLC'S MOTION TO PARTIALLY STRIKE REBUTTAL REPORT OF LINDSEY D. CAMERON, PH.D.** Judge: Hon. Charles R. Breyer Courtroom: 6 – 17th Floor

I, Laura Vartain Horn, declare as follows:

1. I am an attorney at law duly admitted to practice before the courts of the State of California and a partner with the law firm of Kirkland & Ellis LLP, counsel of record for Defendants Uber Technologies, Inc., Rasier, LLC, and Rasier-CA, LLC (collectively, "Uber") in this action. I have personal knowledge of each and all of the facts stated in this declaration and, if called as a witness, could and would competently testify to the facts contained herein.

2. Attached as **Exhibit 1** is a true and correct copy of the October 24, 2025 Rebuttal Report of Lindsey D. Cameron, Ph.D.

3. Attached as **Exhibit 2** is a true and correct copy of the October 12, 2023 Expert Report of Lindsey D. Cameron, Ph.D. for the Office of the Attorney General of the Commonwealth of Massachusetts.

4. Attached as **Exhibit 3** is a true and correct copy of the Under Advisement Ruling, *Coslett v. Hannart*, No. CV 2018-005515 (Ariz. Sup. Ct. Mar. 14, 2023).

5. Attached as **Exhibit 4** is a true and correct copy of the Under Advisement Ruling, *Klosa v. Goldman*, No. CV 2019-000428 (Ariz. Sup. Ct. Aug. 21, 2022).

I declare under penalty of perjury under the laws of the United States and the State of California that the foregoing is true and correct.

Executed on November 5, 2025, in San Francisco, California.

/s/ Laura Vartain Horn
Laura Vartain Horn

E-FILING ATTESTATION

I, Laura Vartain Horn, am the ECF User whose ID and password are being used to file this document. In compliance with Civil Local Rule 5-1(i)(3), I hereby attest that each of the signatories identified above has concurred in this filing.

/s/ Laura Vartain Horn
Laura Vartain Horn

EXHIBIT 1

UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

SAN FRANCISCO DIVISION

IN RE UBER TECHNOLOGIES, INC., PASSENGER SEXUAL ASSAULT LITIGATION

Case No. 3:23-md-03084-CRB

REBUTTAL REPORT OF Lindsey D. Cameron, Ph.D.

This Report relates to the following Wave 1 Cases:
Case No. 24-cv-7940 (B.L.)
Case No. 24-cv-7821 (A.R.2)
Case No. 24-cv-7019 (LCHB128)
Case No. 23-cv-6708 (Dean)
Case No. 24-cv-4900 (WHB 832)

October 24, 2025

Expert Report

prepared by Lindsey D. Cameron, Ph.D.

October 24, 2025

I. Purpose of the Report

1. I have been asked by counsel to provide a rebuttal report and expert testimony in this matter in response to the expert report dated September 26, 2025, authored by Joseph O. Okpaku. I disagree with his opinion regarding Uber's control over drivers as discussed in more detail below.

2. I have been asked by counsel to do the following:
   a. Provide an overview of my rebuttal arguments to Joesph O. Okpaku. (Section III)
   b. Provide an overview of my methodology. (Section IV)
   c. Provide an overview of on-demand labor companies and their operations (Section V)
   d. Provide an overview of organizational control and algorithmic management as it applies to on-demand[1] organizations. (Section VI)
   e. Apply organizational theories on if, and if so how, on-demand companies execute organizational control over their workers and customers. (Sections VII)
   f. Apply theories about sociocultural narratives on if, and if so how, are used by on-demand companies and ride-hailing companies to deploy organizational control over workers and influence their customers. (Sections VIII)
   g. Apply organizational theories on if, and if so how, Uber executes organizational control over their workers and influences their customers in general. (Sections IX)
   h. Assess whether, and if so how, Uber Technologies, Inc., (hereafter "Uber") implements organizational control over workers and influences their

[1] An on-demand organization is an organization that relies on a digital infrastructure to connect workers with customers for short-term assignments in real time—hence the term, "on-demand." (Cameron, 2022:2).

customers/riders, in general, as defined by the literature on organizational theory and organizational behavior. (Overall)

3. As explained below, my opinion is that Uber deploys organizational control through their algorithmic management systems and that this form of control is integral to their business model and is evident in their relationship with their drivers. My opinion is also that Uber also deploys certain narratives to influence drivers' behavior. The basis for my opinion is summarized below. I may revise my opinions further as additional information becomes available to me. I reserve the right to supplement this report.

II. Qualifications of the Author

4. I am an assistant professor of management at the Wharton School of the University of Pennsylvania in Philadelphia, PA. I also hold a courtesy appointment in sociology at the University of Pennsylvania and am a faculty affiliate at the AI (artificial intelligence) at Wharton group. I am a faculty associate at the Harvard Law School's Berkman Klein Center for Internet and Society and a faculty affiliate and prior fellow at the Data and Society Research Institute in New York City. I was also a member (fellow) for the Institute for Advanced Study in Princeton, NJ, the institution of intellectual home of Albert Einstein, Kurt Gödel and Robert J. Oppenheimer, among others.

5. At Wharton, I teach an executive course on the Future of Work and graduate (MBA and executive MBA) class on managing emerging enterprises, such as on-demand companies and technology start-ups. I also teach several doctoral classes on research methods (qualitative methodology) and work and employment relations with a focus on the on-demand economy. At the University of Michigan, I taught an undergraduate class on organizational behavior and organizational effectiveness. I was asked to give remarks to the Joint Task Force on Misclassification of Employees hosted by the Department of Labor, Commonwealth of Pennsylvania, titled "How Digital Platforms are Reconfiguring Work." I have also presented my research in two public hearings held by the Pennsylvania State Senate Democratic Policy Committee on issues relating to algorithmic management, the on-demand economy, and worker classification.

6. Prior to Wharton, I received an undergraduate degree (S.B.) in electrical engineering and computer science from Harvard University in Cambridge, MA in 2005. I received a master's (M.S.) in engineering management, with a focus on crisis, risk, and emergency management, at the George Washington University in Washington, DC in 2009. I was a Provost Fellow at the Wharton School, University of Pennsylvania from 2017 - 2018. I received a Ph.D. in management from the University of Michigan in Ann Arbor, MI in 2020. All my education has included significant research training, and I have completed advanced training in quantitative and qualitative methodology, leadership, and Arabic at the University of Maryland in College Park, MD, the Maryland Institute of Integrative Health, in Laurel, MD, and the American University of Cairo in Cairo, Egypt, respectively. I have been at the University of Pennsylvania since completing my Ph.D. save my one-year at the Institute of Advanced Study. In addition, I spent twelve years working at the National Security Agency (NSA) and Central Intelligence Agency (CIA) as a technical (computer network operations) and an intelligence (counterterrorism) analyst.

7. As an organizational and management scholar, my research is grounded in the disciplines of psychology and sociology. My research program is primarily qualitative and draws on the norms and standards of qualitative methodology in the organizational management field which emphasizes in-depth immersion and observation – to see things from the experiential point of view of actors in the field (e.g., Charmaz, 1996; Glaser & Strauss, 1967; Locke, 2001; Bechky & O'Mahoney, 2015). Hallmarks of qualitative research include long-term (participant) observation, longitudinal interviews, and in-depth analysis of archival documents, such as company materials or web forum postings. Qualitative methods are especially useful for studying emerging phenomena, such as the on-demand economy, because they allow for an in-depth examination of mechanisms and processes. Moreover, research using qualitative methods is among the most impactful, highly cited, and ground-breaking in the field of organizational management, evident in the numbers of awards and citations, as compared to studies that use other

research methodologies (Wang & Reger, 2017; Pratt & Bonacio, 2016; Bartunek, Rynes, & Ireland, 2006; Rynes & Bartunek, 2015; Bansal and Corley, 2011).

8. As an organizational and management scholar, my research is grounded in the disciplines of psychology and sociology. My research program focuses on algorithmic management and on-demand organizations. Given the emerging phenomena, I primarily employ qualitative methods (e.g., participant observation, interviews, document review) that are particularly well-suited for novel phenomena. As a "structural ethnographer" (Burawoy, 2017), my approach to research is worker-centered, seriously considering workers' experience in my analysis to develop broader claims about social structures and processes. I take a granular understanding of how the work is done—examining the interactions between the worker, the organization, and the customers —and I collect data via immersion and comparative work. This approach is rare, even among ethnographers, both because of the difficulty in gaining research access and its time-consuming nature —but it is important. Through immersion, I gain in-depth exposure to how the work process unfolds and, by comparing across settings (workers, on-demand organizations, cities, countries), I can identify mechanisms that cut across said settings. Moreover, it allows me to link the micro—the individual workers' actions—to the macro—sociocultural structures and processes. Together, my methods and data enable me to inductively discover and conceptualize theories that closely reflect the nature of algorithmic management and on-demand work.

9. My academic research is on algorithmic management, with an emphasis on the on-demand economy (colloquially called the "gig economy"). My research program focuses on how algorithmic management shapes organizational structure and processes and how these changes affect workers with an emphasis on the interplay between organizational control and worker autonomy. Since 2016, I have focused on the on-demand economy, with my research including, studying workers on Uber, Lyft, Via, Instacart, TaskRabbit, DoorDash and Amazon Flex, among other gig economy companies, in over eight countries. My data collection includes participation observation (i.e., working in the on-demand economy, being a customer of on-demand services, and observing at organizing

units), interviews, focus groups, archival analysis (e.g., web forums, video logs, and document reviews), surveys, and collecting financial diaries. One core finding across my research is how algorithmic management can seemingly grant autonomy, or a sense of choice, to workers, yet this autonomy is minimal because workers' autonomy is confined to the narrow choices afforded by the management system (Cameron, 2024; Cameron & Rahman, 2022).

10. My research on the ride-hailing industry includes the following data. I spent approximately one hundred hours applying for, training, and working as a ride-hailing driver for Uber in the Washington, DC metro area. A research assistant, trained by me, also drove and collected research data in the Detroit metro area. During this time, I conducted in-depth interviews with drivers about their work routines and career histories. In total I conducted more than 150 in-depth semi-structured interviews (n=63 drivers in North America interviewed over multiple years for a total of 138 interviews with drivers; the remaining interviews were with customers), as well as conversational interviews (n=112 drivers) while riding as a participant observer. I also reviewed public documents by and about Uber, fielded surveys and financial diaries with ride-hailing drivers and spent time on driver forums and at organizations focused on drivers' rights. I have published numerous articles, several award-winning, based on this qualitative and quantitative data, some of which I cite within, (Cameron & Rosenblat, 2020; Cameron, 2022; Cameron & Rahman, 2022; Cameron & Meuris, 2022; Kamaswaren, Cameron & Dillahunt, 2018; Mayberry, Cameron & Rahman, 2024; Cameron, 2024) as well as integrative conceptual and integrative review pieces (Spreitzer, Cameron & Garrett, 2017; Rahman, Karunakaran & Cameron, 2024; Cameron, Lamars, Leicht-Deobald, Lutz, Meijerink, & Mohlmann, 2023; Cameron & Weigel, 2025; Cameron, Conzon & Lam, 2025; Aidinoff, Boczkowski, Cameron, et al., 2024a, 2024b). In addition, I have studied the experience of ride-hailing drivers internationally. Outside of North America, my ride-hailing datasets include interviews with drivers (n=181), field notes from observations (n = 54), forum data, and participants' artifacts. In addition to the ride-hailing industry, my research examines the implications of algorithmic management in other on-demand economy companies, such as Instacart, DoorDash, and TaskRabbit,

and includes a large corpus of interviews (n=224), participant artifacts (n=125), and archival documents (see Cameron, Thomason & Conzon, 2021; Mayberry, Cameron & Rahman, 2024; Cameron, Mayberry, & Maffie, 2025; Cameron, Chan & Anteby, 2022 for examples). I have also compiled an edited volume on the on-demand economy (Cameron et al., 2025a; Cameron et al., 2025b).

11. I have published fourteen academic papers that have been published in several leading management, sociology, psychology, and information systems journals, including *Administrative Science Quarterly, Organization Science, Journal of Applied Psychology, Organizational Behavior and Human Decision Processes, Academy of Management Annals, Annual Review of Organizational Psychology and Organizational Behavior, Journal of Management Insights, Communications of the Association of Information Systems, Communications of the Association of Information System, and Computer-Human Interactions of the Association of Computing Machinery.* (See references for citations.) I am a reviewer at several leading management, sociology, and labor relations journals, including *Administrative Science Quarterly, Academy of Management Journal, American Sociological Review, American Journal of Sociology, Organization Science, Socio-Economic Review, Industrial Labor Relations Review, Sociological Perspectives,* and *Work and Occupations*, and funding institutions, such as the National Science Foundation and the Washington Center for Equitable Growth. I am on the editorial board of *Administrative Science Quarterly* and *Organization Science*, the two top organizations and management journal, and the *Socio-Economic Review*, a leading organizational sociology journal. I have written op-eds in the *Harvard Business Review, The Conversation, Newsweek, Labor and Employment Relations Perspectives, Strategy + People*, and *Fast Company.* I have presented my research on algorithmic management and the on-demand economy in numerous public forums and academic settings, including the Ford Foundation, Aspen Institute, Microsoft, Harvard Law School, Harvard Business School, Stanford Business School, Stanford University's School of Engineering, Massachusetts Institute of Technology, London Business School, Peking University, and the University of Chicago. My research on the on-demand economy has been featured in national and international outlets, such as *Washington*

Post, NPR's *Marketplace*, *CNBC*, *Newsweek*, *Kiplinger's*, *Forbes*, and the World Economic Forum, and has won eighteen (18) national and international awards.

12. A copy of my current curriculum vitae is attached to this report at Exhibit A, which includes more information about my qualification.

13. I have carefully read and considered information provided to me by counsel to form this opinion. The materials about Uber, which are similar in nature to what I typically review in my research about algorithmic management and organizational structure in the on-demand economy and ride-hailing, provided the basis for my opinion in this case. A list of the materials I considered in forming my opinions are identified in Exhibit B. I reserve the right to amend the report and the opinions based on the submission of additional materials and documents, which may influence opinions or allow for different conclusions. The opinions in this report are based on a degree of professional certainty and on a more likely than not basis. A list of other cases in which I have testified as an expert by public hearing, trial, or deposition is attached in Exhibit C. I am being compensated at the rate of $750 per hour. My compensation is not dependent on this opinion or the outcome of this litigation.

III. Summary of Rebuttal Arguments re: Joseph Okpaku's Report

14. I find the analysis and conclusions of Joesph Okpaku's reports incomplete and often inaccurate. Okpaku is not an academic and has not received a PhD (though I acknowledge he has received a terminal degree in his field). To the best of my knowledge, he does not teach doctoral-level courses in any research methodology and has not written any peer-reviewed academic research, let alone research about the gig economy or the ride-hailing industry. I make this point specifically, because much of his report relies not on much peer-reviewed research, but heavily on his own personal observations of Lyft (his former employer), taxicabs, and other ride-hailing companies as well as attending various conferences and reading reports. At best, this makes Okpaku a consumer of research, but not a producer. There is also a difference in quality and

rigor between academic research and the reports that Okpaku often cites. Reports written within and expressly for corporate audiences tend to be less rigorous and have the potential for more bias than academic research. And while someone's personal observations can be interesting, there is a significant difference in quality and rigor between casual and even journalistic observations and the observational methods used in peer reviewed academic research, of which I am an expert in. (See Section I, II and IV.) See Small and Calarco (2022) for more in-depth explanation of conducting, publishing, and evaluating qualitative research.

15. Because Okpaku's report depends so heavily on anecdotal information and lacks a rigorous analytical methodology his report lacks accuracy, validity, and generalizability, all hallmarks of rigorous research. The report makes numerous mistakes that are common for those with a superficial understanding of the ride-hailing industry. A few of these mistakes are discussed as follows.

16. The name of the industry is ride-hailing, not ride-sharing. The term ridesharing refers to the sharing economy, in which exchanges are rooted in social reciprocity. A classic example is a time bank in which individuals would swap services or resources in lieu of a traditional cash economic exchange (Schor and Vallas, 2020, Schor, 2020). At its core, the ride-hailing is an economic exchange with the transactions being mediated by the digital platform's technology. Uber matches workers and customers and sets fares. Uber takes a portion of each fare as well as levying various fees. Uber's algorithmic management controls the labor process hiring, evaluating, and discipline workers. (See Section IX.) Clearly, this is not a time bank among neighbors. Broadly speaking, Uber and on-demand organizations, more generally, use of the word 'sharing' is a co-option of the term meaning implying a more benign, socially embedded exchange of resources than what is taking place. The co-option of the term 'sharing' by Uber and its implications has been discussed in-depth in academic research as well as in the book *Uberland* (2018), written by former Uber employee, Alex Rosenblat.

17. Another example of Okpaku's inaccuracy is that the word 'control' – a key concept in this case -- is not defined in his report. The closest thing to a definition – "A key appeal of ridesharing for drivers has always been the fact that ridesharing allows drivers to completely control when they work" (i.e. are available to provide rides, pg. 21) – is more accurately defined as temporal flexibility of the work shift (Ashford et al., 2007; Pfeffer & Barron, 1988). I recognized this error because one of my theoretical areas of expertise is organizational control and the processes and mechanisms that support organizational control. (See Section VI-VII.) Moreover, this misunderstanding of control is quite common for those with a surface-level understanding of the on-demand economy. Even if we were to exchange the word Okpaku uses – control – with the more accurate work – temporal flexibility – I will argue that workers' temporal flexibility is quite limited. While drivers do have choice on when to log into the app (temporal flexibility in terms of the timing of their shift), their choices are greatly limited once they are logged into the app and subject to algorithmic management and control. (I discuss the relationship between algorithmic management and control in Section VI, VII and IX.) Drivers do not have substantial input into what rides they are matched with, the pickup/destination of the rides, and the length of the ride. I also discuss how this algorithmic management and its control can influence when workers sign into the app, ostensibly the part of the work process in which workers should have the most choice.

18. Okpaku's report states that drivers are free to accept or reject any ride request and may cancel at any time (pg. 21). While drivers are, technically, able to accept/reject/cancel a ride there are consequences that affect workers' standing on the platform. Repeatedly rejecting or cancelling rides affects a driver's rating, access to future trips, algorithmic-based incentives (e.g., surges), and even their ability to stay on the platform. (See Section VII and IX.) In short, many of the statements in Okpaku's state are superficial and taken out context, leading the report to the mistaken and inaccurate conclusion that drivers have complete control over their work when, in reality, they do not.

19. Okpaku states that ride-hailing "drivers have no boss other than themselves" (pg. 21). This is not accurate. See Sections VI-IX about how algorithmic management controls

workers and how narratives of freedom and autonomy are a source of organizational control over drivers (Section VIII).

20. Okpaku cites a 2018 academic study by Hall and Krueger, noting that about two-third of Uber drivers also hold full-time or part-time jobs. Okpaku failed to note that, like himself, that the authors have economic ties to the ride-hailing industry (in this case Uber) and, in part due to this relationship, this research study has been criticized by some scholars. That point aside, a more important issue to consider is what is the most salient measure of Uber's workforce composition and, correspondingly, if this is an appropriate research study to cite. Most tasks completed on the platforms are done by a minority of drivers who are economically dependent and/or work full-time equivalency or more (Koch, 1999; Anderson et al., 2021). Thus, when examining worker composition and work patterns, I argue the more meaningful measure is not whether drivers hold other jobs (outside of ride-hailing) but what proportion of total rides—and therefore company revenue—is produced by a relatively small, highly active subset of workers who are economically dependent on the work. (See Schor et al., 2020 for similar arguments.) Each of these issues brings forth the larger issues that Okpaku has limited expertise in evaluating academic research and building accurate arguments.

21. Okpaku references his personal experiences in Washington, D.C., noting that in 2013 many furloughed federal workers turned to ride-hailing for income and teachers drove during summer breaks. While such anecdotes may certainly be technically accurate, they do not allow for generalizing about the relationship between control, algorithmic management, and Uber. (See opening paragraphs of this section about how personal observations do not equate to academic arguments.) Workers' activities are constrained by the algorithmic management system. Thus, when Okpaku cites Uber's Partner agreement that "We do not, and have no right to, to direct or control you [drivers]" (pg. 25) this is inaccurate, because in practice, algorithmic management systems exercise control over workers. I detail this control relationship at length in this report.

22. Okpapu argues that dynamic pricing gives drivers control over their earnings, since they can choose to drive only when it is most profitable (pg. 27). This conclusion is incomplete and, thus, inaccurate. As I discussed in my report (Section IX), this statement overlooks a central issue: the algorithmic derivation of ride price. Surge pricing is an algorithmic process that determines workers' value and shapes their behavior, thus, limiting drivers' control.

23. Okpapu compares ride-hailing platforms to companies such as Etsy, Ebay, and Airbnb (pg. 27). This analogy is inaccurate, and a common mistake made by those with a limited understanding of the on-demand economy and platform in general. Etsy and Eby are listing platforms, where individuals list goods or services. There is not a labor relationship mediated by the platform. Ride-hailing involved algorithmic management with the labor process—controlling prices, matching, evaluations, and discipline workers (Cameron, Conzon, and Lam, 2025; Cameron and Rahman, 2022; Cameron, 2024). As such the customer reviews used on ride-hailing platforms have a much different and more intensive role than the reviews on listing platforms, as the customer reviews and ratings (alongside other metrics) are integrated in the labor process. (See Section VII and IX.)

24. Okpapu states that rating systems facilitate feedback between riders and drivers, and that ratings are not a mechanism of control. This is incorrect. A long tradition of research in management, organizations, and sociology, documents how evaluation systems – whether through customer ratings, mystery shoppers, or consumer feedback, constitutes a form of control. (See Section V-VII and Cameron and Rahman, 2022.) Ratings mechanism govern drivers' behavior by influencing access to matching opportunities (income), visibility, and continues participation on the platform. While there may be variation in how control is operationalized across labor platforms, platform companies like Uber employ customer ratings as a tool of managerial control (Cameron, Conzon, and Lam, 2025; Cameron and Rahman, 2022).

25. In summary, Okpaku relies on anecdotal rather than scholarly evidence and a superficial analysis of the case at hand. This results in a misunderstanding of fundamental concepts of organizational control, algorithmic management, pricing, customer ratings, and platform design and governance which, in turn, leads to inaccurate conclusions about control in the ride-hailing industry, in general, and Uber specifically. I discuss these issues more in-depth below.

IV. Methodology

26. I am an academic researcher with expertise in qualitative and quantitative methodology. I received my PhD at the University of Michigan (2020) and have taken methods courses at the graduate/doctoral level at the University of Michigan and University of Maryland and at the undergraduate level at Harvard University. I currently teach doctoral-level research methods classes in my methodological area of expertise, qualitative research methods. Qualitative research includes the collection and analysis of textual and visual data and includes observation (participation and non-participation), interviews, and visuals and/or text analysis from various sources (e.g., discussion boards, media articles).

27. As an organizational and management scholar, my research is grounded in the disciplines of psychology and sociology. My research program is primarily qualitative and draws on the norms and standards of qualitative methodology in the organizational management field which emphasizes in-depth immersion and observation – to see things from the experiential point of view of actors in the field (e.g., Charmaz, 1996; Glaser & Strauss, 1967; Locke, 2001; Bechky & O'Mahoney, 2015). As a "structural ethnographer" (Burawoy, 2017), my approach to research is worker-centered, seriously considering workers' experience in my analysis to develop broader claims about social structures and processes. I take a granular understanding of how the work is done—examining the interactions between the worker, the organization, and the customers—and I collect data via immersion and comparative work. My research on the ride-hailing industry includes the following data. I spent approximately one hundred hours applying

for, training, and working as a ride-hailing driver for Uber in the Washington, DC metro area. A research assistant, trained by me, also drove and collected research data in the Detroit metro area. During this time, I conducted in-depth interviews with drivers about their work routines and career histories. In total I conducted more than 150 in-depth semi-structured interviews (n=63 drivers in North America interviewed over multiple years for a total of 138 interviews with drivers; the remaining interviews were with customers), as well as conversational interviews (n=112 drivers) while riding as a participant observer. I also reviewed public documents by and about Uber, fielded surveys and financial diaries with ride-hailing drivers and spent time on driver forums and at organizations focused on drivers' rights. In addition, I (along with local research assistants) have completed more than two hundred interviews of Uber drivers in Nigeria, Ghana, Brazil, India, Germany, Spain, and the UK along with participant observation. In addition, I have studied hundreds of gig economy workers on other platforms such as TaskRabbit, DoorDash, Instacart, Upwork, and YouTube. I have published more than a dozen peer-reviewed academic papers on the gig economy and received more than a dozen best-paper awards, both national and international.

28. I used a similar research methodology – grounded theory (Glaser & Strauss, 1967; Charmaz, 2006) -- in creating this report as I do in an academic research project. This iterative process includes reading materials carefully, iterative open and focused coding, creating analytical categories, writing memos, engaging in academic conversations, and drafting reports.

V. Overview of On-Demand Labor Organizations and their Life Cycle

29. At the most basic level, on-demand labor companies are an intermediary that connect workers and other parties (e.g., customers, clients, merchants) to facilitate an economic exchange. Yet on-demand labor companies are much more complex than traditional intermediaries (e.g., LinkedIn, taxicab operators, staffing agencies) due to their organizational structure, socio-technical processes, workforce composition, and the outcomes these systems produce. For example, besides matching labor and supply the

algorithmic management system of platform organizations can determine workers' pay rates, what customers are charged, and can evaluate workers' and customers' behaviors. This is substantially distinct from information providers like eBay, LinkedIn, and outplacement agencies in which the organization's role ends once workers and customers are acquainted and the technology, if present, is relatively simple and does not manage and control workers' behaviors (e.g., eBay's average five-star rating). In a review of the on-demand literature, Vallas and Schor (2020) conceptualize platforms as permissive potentates that have externalized responsibility and control over economic transactions (often to customers) while still exercising concentrated power. Due to distinctions such as these organizations "represent a distinct type of governance mechanism, different from markets, hierarchies, or networks, and therefore pose a unique set of problems for regulators, workers, and their competitors in the conventional economy" (Vallas & Schor, 2020: 548).

30. This remainder of this report provides details about how on-demand labor companies are distinction from traditional intermediaries due to their business model, control processes, algorithmic management system that exercises relationship, and the sociocultural narratives used to engage workers.

31. *The On-Demand Organization's Lifecycle.* Many founding narratives of on-demand companies trace their origins to the sharing economy – Airbnb advertised they helped people find friends to stay with in new cities and Uber offered to help drivers to earn while making use of idle resources (Sundarajan, 2016; Schor, 2020). As Schor (2020) explains, the actual mechanisms of running these companies quickly morph far beyond their (purportedly) sharing motives. When an on-demand company initially starts, it must attract parties to offer and purchases services on their platform. By creating network effects, in which a product or service gains additional value as more individuals use it, platforms are able to secure market dominance and secure profitability. In the early stages of the organization's lifecycle, they must recruit workers and customers/clients to their platform and might subsidize the acquisition of workers to a platform through referral bonuses, subsidized services, or morale-boosting activities. For

example, in Uber's early years they offered drivers free iPhones and ice cream parties as well as subsidizing customers initial rides (Issaac, 2018; Rosenblat, 2018). While these initial outlays to create network efforts are costly, with firms initially making big losses, they can ultimately create value for the firm as they lock in workers and customers allowing them to outcompete rival firms and lock in workers and customers.

32. As already described, in the early stages of a platforms organization's lifecycle they often favor workers and customers to create network effects, even subsidizing the costs of the services. As these organizations gain market dominance, they may shift their activities towards workers and customers to capture more value to make up for initial losses and start making profits. This process, in which there is a slow degrade of the functionality of the platform, is called platform decay or enshitification (Doctrow, 2023). Doctrow describes the process of enshitification as: "First, they are good to their users; then they abuse their users to make things better for their business customers; finally, they abuse those business customers to claw back all the value for themselves. Then, they die."

33. Platform decay is possible when a platform has a monopoly or near-monopoly status (e.g., duopoly) in its sector and its user base becomes accustomed to its services. Examples include shoppers on Amazon, teenagers reliant on TikTok for their media consumption, homeowners who are economically dependent on Airbnb rentals, and Uber and Lyft riders who get rid of their car and rely on ride-hailing services as part of their daily commute. With a captive audience of workers, customers, and other parties, platform organizations have the freedom to change the terms and conditions of their agreements with their base and securing larger amounts of value.

34. The theory of platform decay helps us understand seemingly contradictory actions within platform organizations. In the early stages of a platform, securing enough workers is crucial which can result in referral bonuses, incentives, high wages, and little friction in gaining access. In other words, there may be more favorable terms offered to drivers earlier in the platform organization's tenure. Concurrently, customers are crucial

to the platform organization, as they bring in revenue, and customers have sensitivity to prices the platform organizations might have to have more dynamism or elasticity around prices at certain times (e.g., during on-peak times). In other words, there may be favorable terms offers to customers earlier in the tenure with the platform organization (to get them hooked, so to say) or during certain time periods (e.g., off-peak periods) that may be irrespective of where the company is in its life cycle. Taken together, this suggests that when value creation which be most important and to which party will vary based on several factors.

35. Research shows there are two crucial points where drivers may leave ride-hailing: on-boarding, after the first ride, or after significant rides. Ride-hailing companies have high churn rates, with fifty to ninety-six percent annual turnover (Hall & Krueger, 2015; Huet, 2015; Isaac, 2018; Rosenblat, 2019). Given the costs in recruiting and on-boarding a driver, addressing driver churn, or keeping drivers on the platform longer is important for capturing value and earning more money (Huet, 2015).

VI. How Organizational Scholars Define Organizational Control and its Importance

36. As an organizational and management scholar researching the on-demand economy and on-demand organizations, a major focus of my research is on organizational control. Control is one of an organization's primary functions (Fayol 1949) and the "most fundamental problem" (Van Maanen & Barley 1984: 290) they face. The challenge is that organizations must obtain cooperation among individual workers who share only partially congruent goals with the organization, thus organizations must attempt "to increase the probability that individuals will behave in ways that will lead to the attainment of organizational objectives" (Flamholtz, Das, & Tsui 1985). In the management and organizational literature, organizational control is defined as any process that aligns an individual worker's "capabilities, activities, and performance with the organization's goals and aspirations" (Cardinal, Sitkin, & Long 2004: 411).

37. Conceptually, there are two dimensions of organizational control: general and detailed (Edwards, 1986). General control refers to the overarching "accommodation of workers

to the overall aims of the enterprise" (Edwards, 1986: 6) and can include broad organizational processes such as hiring, socialization, or how bureaucratic structures shape information flow. In contrast, detailed control refers to the organization's control over the execution of the work itself, including the pace of work, allocation of tasks, performance evaluations, and discipline. Organizations must balance general and detailed control measures to maintain a motivated workforce and ensure profitability (Friedman, 1977). In other words, over-prescribing elements of detailed control (for example, how long workers on the assembly line can go to the bathroom) may undermine general control in that workers may become disgruntled. Thus, organizations tend to rely on incentives or "carrots" more than punishments or "sticks" so that workers align their efforts with managerial objectives and goals.

38. Organizational control is critical for any organization because it ensures that workers' efforts are aligned with managerial goals and objectives. Organizational control is especially important for on-demand companies. First, on-demand companies often consider their workforce to be independent contractors. As such, to elicit these workers' participation, on-demand organizations rely on algorithmic management systems and customer control. But these practices, which distance the organization's control practices from its workers, often obfuscate the organization's actual relationship with workers, in essence, laundering control.[2] Second, the organizational strategy of most on-demand companies is to secure market dominance before achieving profitability.[3] For on-demand organizations, capturing market share means that they must attract a significant customer base and, correspondingly, workers to serve this customer base to ensure that services are delivered 'on-demand.' In practice, this manifests as a set of organizational practices and policies to try and keep customers satisfied (i.e., a customer-centric business model) and to try to get workers on the app, available to work, especially

[2] Classification is especially relevant in closed labor market platforms, such as Uber, Lyft, and Instacart, in which algorithmic management much more heavily directs and controls workers' actions, as opposed to open labor market platforms, such as TaskRabbit and Upwork.

[3] This process is also referred to as achieving a "network effect," where the value of the on-demand company increases based on the number of people who use that product or service increases (Rahman, Karunkaran & Cameron, 2024a; Cusumano, Gawer & Yoffie, 2019).

during high-demand periods (i.e., via algorithmic management systems, directives, and nudges to influence workers' behaviors). Moreover, on-demand organizations will often regularly experiment on their workers and customers, testing out new products and features, to inform potential strategic choices (Rahman et al., 2023). Taken together (and as explained in greater detail below), these two factors help explain why getting organizational control 'right' is so crucial for on-demand organizations—it is both pivotal to on-demand companies' quests for market dominance and must also be obscured to a large majority of its workers.

VII. How On-Demand Organizations Exercise Organizational Control through Algorithmic Management

39. On-demand organizations combine both old and new elements in their business. On-demand work combines two features from early capitalism system: the spot labor market system (e.g., having workers show up at a given location, such as a dockyard, and being hired on the spot for a day) and the putting out systems (e.g., when workers would complete garment work at home for a fixed price per piece). All on-demand organizations rely on having a readily available workforce pool, ready to work "on-demand." And most on-demand organizations pay workers a set price for a task whether this price is set by the customer (e.g., open-labor markets such as Upwork in which workers' skills are more specialized) or the on-demand organization (e.g., closed labor markets such as Instacart and Uber in which workers' skills are more generalized). Moreover, at their core on-demand organizations are one of the oldest organizational forms: a customer service organization dedicated to serving and prioritizing the needs of their customers (Graham & Woodcock, 2020; Cameron & Rahman, 2022). While gig work is sometimes described as "not new" – musicians, for example, have always done gig – one thing that is unique about on-demand organizations is that there no possibility for career advancement. Musicians can steadily increase their skill, raise their rates and add new members to the band. This is not the case in organizations such as Uber in which a driver who has been driving for three days or three months or three years will receive the same base compensation and there is no pathway to being an employee

within Uber corporate. While drivers may be able to increase their tip income through excellent customer service tips are outside of the base wage and are a discretionary and volatile income source. Thus, at Uber, drivers have no real way to increase their base wages based on skill.

40. The most unique feature of on-demand organizations is their algorithmic management system. Algorithmic management systems are "a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process" (Duggan et al., 2020: 119). Deeply intertwined with society, algorithmic management systems are what science and technology studies scholars call *sociotechnical*, a term that calls attention to how values, institutional practices, and inequalities are embedded into the code, design, and use by the authors of the code.

41. When studying algorithms and algorithmic management systems it is important to note that, like data (Gitelman, 2013), algorithms are constructed. Heiland (2023) describes the four levels of construction. First, an algorithm is designed and planned such that it meets the needs of the organization. Second, the algorithm is programmed by programmers who place a "particular philosophical frame on the world that renders it amenable to the work of code and algorithms' (Kitchin & Dodge, 2011, p. 247)." Third, algorithms are curated by 'data janitors' (Kellogg et al., 2020: 387) which correct erect and make injunctions in the algorithm's process. And finally, those who interact with the algorithms also participate in the construction such that algorithmic decision only becomes effective through usage.

42. Due to this social construction, seeing and analyzing the source of code would not provide sufficient insight into understanding the technology. Indeed, such an approach conceptualized algorithms as isolated and objective entities which, as described above, is simply not the case (Heiland, 2023; Christin, 2020). Algorithmic management systems reflect and embody broader socio-cultural values and can never be seen as socially or politically neutral or "just a tool" (Orlikowski, 2007; O'Neill, 2006; Joyce et al., 2021).

In the remainder of this report, I explain the sociotechnical features—the values, institutional practices, and inequalities—that are embedded within the algorithmic management system of Uber. As I explain, Uber has designed their algorithmic management systems, to exercise ever-increasing organizational control over workers' behaviors while also obfuscating the companies' intent and inherent power in the platform-worker relationship.

A. Four Components of Algorithmic Management That Lead to an Intensification of Organizational Control

43. Like traditional organizations, on-demand organizations rely on a combination of general and detailed control to align workers' behaviors and efforts with organizational goals and objectives. One distinction between traditional and on-demand organizations is that on-demand companies rely on keeping an always-ready workforce available on-demand. Unlike traditional organizations which rely on human managers to implement control, on-demand organizations rely on algorithmic management systems. Algorithmic management systems assist on-demand companies in maintaining and controlling an always available workforce. Under these algorithmic management systems, algorithms, rather than human managers, perform managerial tasks such as hiring, evaluating, and rewarding/disciplining workers (Lee et al. 2015; Danaher 2016; Rosenblat 2018; Shapiro, 2018; Wood et al., 2019; Cameron 2024; Kellogg et al. 2020; Schor 2020; Vallas & Schor 2020).[4] As explained below, these algorithmic management systems control workers' behaviors through organizational design, continuous surveillance, swift punishments, and the effective deployment of incentives and nudges (Thelen, 2018; Mohlmann et al., 2021; Rahman, 2021). While all organizations, to some extent, exercise control over their workers, the algorithmic management system that the on-demand business model relies upon is even more "comprehensive, instantaneous, interactive, and opaque" (Kellogg et al. 2020: 366) than other management systems, resulting in an unprecedented quantification and intensification of organizational control

[4] While some organization may use algorithms, alongside human managers, as part of their management system (e.g., hiring, see Ajunwa, 2023 for a review) this is distinct from algorithmic management systems which are more comprehensive in which algorithms perform (nearly) all managerial functions.

over workers. Some scholars have gone as far to call the control exercised by on-demand organizations as an "invisible cage" because they implement a form of organizational control in which the criteria for success are largely invisible to workers and changes to those criteria are unpredictable, made solely by the organization itself (Rahman, 2021).

44. Several features contribute to the intensification of control by algorithmic management systems. First, algorithms are engineered by organizations to use quantified metrics to comprehensively monitor and track workers' minute movements. Embedded in cameras, biometrics trackers, and sensors, algorithms record workers' physical movements to prove adherence to the rules and regulations of the organization, such as by verifying worker identities (e.g., Rogoway 2020; Zuboff 2019), tracking drivers' location (Levvy, 2022; Viscelli, 2018), acceleration rate and braking speeds for workers operating motor vehicles (Clemes et al. 2014; Thorp et al. 2012), and monitoring emails to assess mood and productivity (Goldberg et al. 2016; Leonardi & Treem 2020). In ride-hailing, telemetrics monitor workers' driving activity (e.g., location and braking speeds) which can then be input into an algorithmic management system determining worker's work opportunities or incentive offers. And photo verification systems verify drivers' identities and ensure compliance with system rules, such as wearing masks during the COVID-19 pandemic (Watkins 2021, 2023). Overall, the quantification of worker's actions allows for the generation of fine-grained, granular information that can then be inputted into the algorithmic management system further intensifying the system's control over workers.

45. Second, algorithms are designed to collect data from the organization's workers and feed that information back into the algorithmic management system, allowing the system to improve its own efficiency by increasing managerial knowledge and organizational control over workers. On-demand organizations are customer service organizations, in that they facilitate exchanges between customers and workers. "The customer is king" is a common refrain among service organizations, emphasizing their mission to prioritize customer satisfaction. Indeed, many functions performed by the algorithmic

management system are meant to do exactly that, prioritizing customers over workers. For example, on-demand companies, such as TaskRabbit and Upwork, can change how search results of worker profiles are presented to customers based on real-time feedback from customer comments, number of page views, and worker performance (Alkhatib & Bernstein 2019; Gillespie 2018). The changes allow the company to increase the probability of a successful match between customers and workers, satisfying customers' needs, and ultimately, keeping and attracting their customer base. Often, workers are unaware of the changes accomplished by the algorithmic management system and their implications for their economic livelihood (Irani & Silberman, 2013; Rahman, 2021). In ride-hailing, companies can, and often do, instantly suspend drivers' access to the app or assign them a less profitable ride after a customer complaint, doing so even before the complaint is investigated, and the driver has an opportunity to present their own version of events (Cameron, 2022). Such actions favor the customer over workers, supporting the on-demand organization's customer-centric business models. On-demand organizations can collect information about workers whether they are logged into the app and use this information to optimize their own operations and/or to try to influence workers' and customers' behaviors in some way. Ultimately, on-demand organizations rely on worker data for their business model to work.

46. Third, algorithmic control is more interactive than previous forms of organizational control because algorithms enable interactive participation from multiple parties in different locations and on-demand organizations can use this information to run experiments. On-demand apps, for example, allow workers to compete across multiple zones for assignments and communicate in real-time with customers (Shevchuk et al. 2018). This often results in workers staying on-line to work on the app at strange hours, which is precisely one of the goals of an on-demand organization—to have an always available, on-demand workforce (Schor et al., 2020; Cameron, 2024). Moreover, on-demand companies have collected data about their workers' activities on competitors through data brokers or third-party analytics services (Isaac, 2017; Isaac & Lohr, 2017; Isaac, 2019). The fine-grained, granular information from brokers can then be inputted

into the algorithmic management system further intensifying the system's control over workers.

47. Many on-demand organizations run experiments on their workers, to which workers are invisible to, pertaining to various aspects affecting work conditions, including changing their visibility in algorithmically mediated search results, how workers' profiles are presented to customers, giving feedback about their ratings, or giving automated communications to deter certain behaviors (Rahman, Weiss & Karunkaran, 2023). Workers are often unaware of the specifics of the experiments that are being run on them and how it is shaping their work opportunities and incentives further intensifying the system's control over workers.

48. How these experiments are run are based on whether the on-demand organization is an open-labor market platform and closed-labor market platform. In open-labor market platforms, such as Upwork and TaskRabbit, customers and workers choose one another, often from an algorithmically curated list, to work on a mutually agreed upon tasks. By contrast, in closed-labor market platforms, such as Uber, Lyft, and Instacart, the organization's algorithmic management system matches customers and workers to complete specified tasks. In addition to the matching process, these labor markets differ in that closed labor markets have more direct influence on the work opportunities presented to workers, their pay rates, and if they are even allowed to stay on the platform at all.

49. On open-labor platforms, experiments may include changing how workers' profiles, descriptions, and ratings are presented to customers (e.g., Rahman et al., 2023; Curchod et al., 2021). For example, platform companies experiment with how workers' ratings are calculated, how prominently ratings are displayed to workers (if at all), and how they match customers with workers (Rahman et al., 2023; Ticona & Matescu, 2020). In these instances, particularly where there is a robust on-line community, workers may know they are "guinea pigs" in experiments but are generally unaware of the experiments' specific terms (Rahman et al., 2023). In contrast, on closed labor platforms, workers are

generally unaware that there are any experiments whatsoever. In ride-hailing, for example, companies can automize drivers and routes at the city-level, in ways that are unobservable to drivers. These workers are either unaware that there are experiments, in general, or of the specifics of any experiment (e.g., the terms, their role, the results, how their data is being used to nudge their behaviors in even more complex ways). Alex Rosenblat, the author of *Uberland: How Algorithms are Rewriting the Rules of Work* states, "Because drivers don't really expect to be the subjects of A/B testing, such as when the company tests one version of an app feature on some drivers and another version on other drivers to evaluate which one preforms better: the experimental practices that might work on everyday consumers on the Internet have different consequences in the workplace at Uber" (Rosenblat, 2018:15).

50. Moreover, given that work on closed labor market platforms is generally locationally dependent (e.g., completed in-person), these workers are less likely to be active in on-line communities that would promote information sharing among themselves (Cameron, 2022). This lack of visibility makes it impossible for drivers to effectively compare the details of their rides they perform (types, fare amounts, speed of matching) to those being assigned to their fellow drivers, leaving them to question the integrity of the algorithmic management system (Cameron, 2022; Rosenblat, 2018). In the face of unknowable experiments, workers often rationalize their diminished autonomy as a "business as usual" aspect of work life on the platform (Rahman et al., 2023).

51. Fourth, algorithms are often more opaque than previous forms of organizational control because the data and algorithms used to control workers are usually proprietary and undisclosed (Burrell 2016; Orlikowski & Scott 2014). And even if individuals had the ability to examine the algorithmic code, such information would likely be indecipherable (Noble, 2018; Christin, 2020). This opacity promotes an information asymmetry between workers and the organization, as workers are unaware of what data is being collected and how the on-demand company uses worker-related data to make decisions that affect them (Rosenblat & Stark 2016). For example, drivers are unaware if and/or how customer ratings and telemetric scores may affect future rides offered to them,

leaving drivers completely surprised when they are suspended from the app (Cameron, 2022; Rosenblat, 2018).

52. These four components of algorithmic management systems—quantification of metrics, instantaneous feedback, their interactive nature, and their opaqueness—lead to a intensification of organizational control in on-demand organizations as compared to other organizational forms (Aneesh, 2009; Kellogg et al., 2020; Vallas & Schor, 2020). By capturing fine-grained data about workers and customers, on-demand organizations can more effectively design a management system that more effectively "captures" (Noble, 2018) workers' attention and nudges them into making decisions that are in alignment with organizational goals. Algorithmic nudges can be quite persuasive in guiding worker behavior. Möhlmann (2021) notes, "with so much data about workers' behavioral patterns at their fingertips, companies can now develop personalized strategies for changing individuals' decisions and behaviors at a larger scale. These algorithms can be adjusted in real-time, making the approach even more effective." Remarking on the effectiveness of the algorithmic management system and the market dominance of Uber, Iwan Barankay, an economist at the Wharton School, aptly summarized this degree of organizational control, explaining that "Whatever Uber does, they can get away with it because there's very little push back from the other side. Much of the inner-working of these management systems are obscured from workers, such that they are unaware to the extent of which the power and information of the worker-platform company relationships is biased toward protecting the interests of the platform and customers over workers (Chai & Scully, 2020).

B. How On-Demand Organizations Exercise Organizational Control Through Algorithmically Mediated Customer Control

53. On-demand organizations are customer service organizations. In these type of organizations, frontline workers are essential to the organizations' desire to satisfy customers because they directly interact with the organizations' customers regularly (Leidner 1993, Batt 1999, Korczynski et al. 2000). To ensure that service workers

behave in ways that are consistent with the organization's objectives, organizations curate workers' behavior through "service rules" and "feeling scripts" in which certain behaviors are emphasized, such as cheerfulness for Disneyland Park attendants or friendliness for flight attendants (Van Maneen 1991; Hoschild 1983). When these rules are violated, workers can receive poor evaluations and face sanctions, such as being forced to take remedial training, being transferred to lower-paid "backstage" work, or even being terminated.

54. While service organizations have always used customers to monitor workers, such as through mystery shoppers, on-demand organizations are unique in the extent to which they outsource performance management to customers and use algorithmic management to collect that data and then influence worker behavior. In on-demand organizations, this outsourcing of organizational control to customers is so complete that scholars describe it a "laundering control" (Maffie, 2022) because customers, ostensibly, are the ones evaluating workers when it is actually the on-demand organization that is directing and controlling the entire labor exchange and then using the results for its own business purposes. Guidelines—posted on on-demand companies' websites, YouTube channels, and Instagram feeds—offer suggestions of appropriate behaviors. Workers reported being so pressured by these suggestions that they would take on additional physical risk during dangerous events, such as the COVID-19 pandemic, to keep customers satisfied (Cameron, Thomson & Conzon, 2021). Even as customers have control over workers, through the ratings process, actual power is still exercised by the platforms' algorithmic management system (Cameron & Rahman, 2022; Kellogg et al., 2020).

55. On-demand organizations integrate customer control into their algorithmic management systems. They match workers with customers and compute workers' overall evaluation scores and they outsource the task-by-task monitoring and evaluation of interactions to customers (Shapiro 2017, Wood et al. 2019). In algorithmically mediated customer control, these companies use "customers as an additional layer of managerial control by empowering customers to direct, monitor, and/or evaluate workers" (Maffie 2020, pg. 5). The algorithms then track these ratings, computing an overall score for workers that

then affects workers' access to future work assignments (Rosenblat 2018, Ravenelle 2019, Schor et al. 2020; Cameron & Rahman, 2022). Workers with lower ratings, for instance, may have lower visibility in platforms' search results, be matched more slowly to incoming assignments, or lose access to the platform (Leung 2014; Pallais 2014; Rahman 2021; Rahman 2024). Customers and workers cannot see the ratings and feedback that each party provides about the other until both parties complete the feedback process and, at times, may not be able to assign a rating to a specific interaction. Although workers rate customers, in practice, these ratings are largely meaningless, as workers often state they universally give customers perfect ratings to signal to future customers that they are easy to work with and to keep the work process functioning smoothly (i.e., not wanting to spend extra time providing feedback for a sub-five-star ride; Cameron & Rahman, 2022; Rahman, 2019).

56. How an on-demand organization exercises algorithmically mediated customer-control, and the visibility of its algorithmic management systems is dependent on if it is an open or closed labor market platform. In open labor market platforms (e.g., TaskRabbit, Upwork), customers have full discretion to choose the freelancers to work on their projects; however, the app's matching algorithm facilitates this process in two ways (Leung, 2014; Rahman, 2021; Cameron et al., 2021). First, customers can enter keywords into the organization's search engine (e.g., "design a video game," "hang pictures") and/or use the filtering criteria (e.g., rating thresholds, location, earnings, experience) to refine their searches. Then the companies' matching algorithms present customers with a list of freelancers they can invite to apply for their job. Alternatively, customers can submit a project description and preferred freelancer qualifications (e.g., desired level of experience, skills required) and the matching algorithms will suggest freelancers to customers and projects to freelancers. Freelancers are free to work on multiple projects simultaneously, and customers can hire multiple freelancers to work on the same project. For on-demand companies like Upwork, for example, when a project is done, the customer rates the worker on a scale of one to five along six dimensions—availability, communication, cooperation, deadlines, quality, and skills (Rahman, 2019). These ratings are highly visible and prominently displayed next to users' profile names

in search results. Search results may also suggest specific freelancers to customers based on their ratings and offer incentives, such as bonuses or reduced commissions, based on their ratings. If workers' ratings fall below a certain threshold, they may no longer be featured in the search results. Moreover, algorithms or other technology monitor workers' behaviors, such as via automatic screenshots or keylogging, to ensure that workers are behaving in ways that are in alignment with the objectives of both the organization and the customer (Ajunwa, 2023).

57. As compared to open labor market platforms, in closed labor markets platforms (e.g., Uber, Lyft, and Instacart), algorithmic management is more deeply embedded into the labor process and more prominent for both workers and customers, signifying a greater level of algorithmically mediated organizational control. Once workers have logged onto the app, they are algorithmically matched with tasks using a process that is not visible to workers (i.e., workers are unaware on the factors that match them with a given rides). Matches are meant to optimize the marketplace (Lee et al., 2015; Mohlmann et al., 2021). In ride-hailing, for example, a company's matching algorithm considers factors such as, customer ratings, physical proximity to the customer, acceptance and cancellation rates, routing, predicted demand near rider destination, vehicle and ride type requested (e.g., luxury rides) (Rosenblat, 2018). Yet because matching is set for network optimization, matches do not always prioritize individual workers' preferences.

58. In both open and closed labor markets, workers are often evaluated by customers on a five-point scale and/or telemetrics. In ride-hailing, for example, at the end of every ride, customers rate the ride, and the algorithm uses this rating to calculate an overall score based on the driver's ratings over a past set of rides (Cameron & Rahman, 2022; Cameron, 2024; Rosenblat, 2018). For drivers focused on the service of driving, delivering high-quality service and, in general, remaining in good standing on the app, these ratings score help ensure that workers abide by on-demand companies service rules and scripts, in that workers exhibit behavior that is pleasing to customers. Ratings are highly visible, and workers can see them immediately upon logging into the app; however, workers cannot see which specific customer provided which feedback

(Cameron & Rahman, 2022). If ratings fall below a certain threshold workers can be asked to take remedial training and/or be blocked from logging into the app, which essentially equates to being fired. In Instacart, for example, shoppers may not be eligible to get shopping blocks during the most lucrative times if their ratings are not high enough (Cameron, Chan & Anteby, 2022). Algorithms and telemetrics monitor workers' behaviors, often via screenshots and gyromagnetic sensing, to ensure that workers behave in ways that are in alignment with the objectives of both the organization and the customer. Workers are sent warning messages and can be blocked from logging into the app if they do not meet the company's metrics and may lose access to preferential loyalty programs, such as Uber Pro and Lyft Rewards (Rosenblat, 2018).

C. **How On-Demand Organizations Influence the Behaviors of Customers**

59. On-demand organizations shape the actions of its clients and customers. One of the most striking ways it shapes customer behavior is by creating a permissive environment in which customers encounter little, if any friction, in their service transactions with the platform. In part, this permissiveness is because of the importance of customers in the on-demand economy's business model and for venture capital-backed technology companies more broadly. Venture capital is a form of private equity financing provided by firms or funds to emerging companies, that have been deemed to have high growth potential. Typically, the expectation is that only about one in ten (10%) will succeed, i.e., offer 100x or more returns by the time of the fund's exit, which is typically five to ten years. This financing structure, which is near-ubiquitous for on-demand companies, places tremendous pressure on on-demand companies to grow their user base as quickly as possible, even at the expense of profits (Shestakofsky, 2024). Indeed, many on-demand companies subsidize their services for customers to attract more users and geographically scale.

60. This has led to widespread issues around fraudulent accounts and customer fraud (Ticona, 2023; Watkins, 2022). Often these fraudulent accounts can be linked to mistreatment of workers by customers (Taylor, 2024). Customers' ratings of workers are

meaningful and affect several outcomes on the platform which has already been discussed (e.g., future task assignments). However, on many platforms workers do not rate customers and, if they do, these ratings are ceremonial and not used in any meaningful way. For example, ride-hailing companies claim that workers will not be matched again with customers they have given low ratings; however, given the size of ride-hailing marketplaces this indication of a low-quality interaction would not significantly affect the customer's ability to obtain future rides.

61. At the granular level, on-demand companies structures worker behaviors at the app interface which structured how customers request tasks, pay, and rate their services. Moreover, through guidebooks (e.g., Uber's community guidelines, Shipt's the Hub) and the five-star rating system the on-demand organization sets the customers' service expectations and what they should be attuned to in the behaviors of workers.

62. In addition, when there is a problem on-demand companies often defer to customers offering them credits or discounts. This deference can influence customers to use the platform again because there was a positive resolution to their issue. For example, when an Uber or DoorDash customer complains about their order, a series of automated prompts determines their refund amount. Similarly, on Uber, when customers complain about a service encounter drivers' accounts are often frozen until the investigation is complete, leaving workers bereft of income (Cameron & Rahman, 2022). And on Shipt, when drivers cause issues or damages for customers (e.g., running over hedges, forgetting an item) it is the on-demand company that provides compensation, ensuring that customer satisfaction remains high.

63. On-demand organizations also shape the conditions around the service encounter, such as the location of the service encounter and surveillance surrounding it. Be design, closed-labor market companies, such as Uber and DoorDash, dictate where the work will occur by design. For example, workers on ride-hailing apps complete their tasks in a car and on package delivery apps workers complete their tasks and stores. On-demand organizations also determine any surveillance and control mechanisms to be used during

the service encounter, such as cameras or audio recordings. Upwork, for instance, provides clients with a visual record of a worker's activity by capturing randomized screenshots approximately six times per hour (Jarrahi and Sutherland, 2019). Similarly, Uber has been offering subsidized dashcams to workers to monitor in-car activities (Kaplan, 2023).

D. How On-Demand Companies Use Algorithmic Management to Obfuscate Their Organization Control Over Workers

64. One way that organizations can avoid fueling worker resentment and resistance is to superficially provide workers with a sense of autonomy while also imposing significant constraints—that is, allowing for some worker discretion, within boundaries provided by the organization (Friedman 1977; Cameron, 2024). Wood and Lehdonvitra (2021) call this "subordinated agency." As I describe below, ride-hailing companies like Uber are constantly balancing these tensions — directing workers' behaviors through algorithmic management systems, but not so much that drivers balk at the companies' goal of keeping drivers on the app. In this section I describe three practices that ride-hailing companies use to promote a false sense of autonomy for drivers on the app—constant and confined choice, gamification, and workplace games—each of which serve to further enmesh workers into the on-demand company's algorithmic management system of control.

65. *Constant and Confined Choice:* Algorithmic management scaffolds drivers work activities such that workers are afforded a set of constant and confined choices. The algorithmic management system provides a set of choices that are narrow, such as the choice to accept a ride, the choice to which rate a rider, and drivers can make hundreds of these choices within a short period of time. Workers' behaviors align with two dominant tactics (Cameron 2024). In *engagement tactics,* drivers interact with the algorithmic management system within its boundaries: they make decisions about what rides to accept, when, where, and for which company to work for, and they usually adhere to nudges. In *deviance tactics*, by contrast, drivers manipulate the algorithmic management system by pushing against its boundaries: they decline certain rides and try

to inflate fares to obtain desired rides, for example. These actions, if detected, are penalized, but the sanctions can often be easily countered (Cameron, 2024). While the behaviors associated with these two tactics are practical opposites, they both contribute to workers' sense of autonomy in part because workers perceive themselves as skillful in being able to navigate the algorithmic management system. Yet the reality is that the workers' choices are constrained, coming from a predefined option set mediated by (and within the boundaries of) the algorithmic management system. Even drivers' deviant behaviors and the subsequent workarounds (e.g., drivers declining multiple consecutive rides and then requesting themselves as a rider from another phone) can be within the boundaries of the system since this leniency has been programmed, literally, into the algorithmic management system (Cameron, 2024). Taken together, this suggests that these tactics reinforce the idea for drivers that they have choice while leaving organizational control in the on-demand economy in the hands of the on-demand organization itself.

66. *Gamification.* Another way organizations obfuscate control is by gamifying work, or applying elements of game playing (e.g., point scoring, competition with others) to work activities to encourage workers to work longer hours. By gamifying work, the work itself becomes more fun and enjoyable while ensuring that workers' behaviors are aligned with the organization's interests—with the result being that workers are controlled. Numerous scholars describe the gamification and psychological priming practices on ride-hailing and other on-demand apps (e.g., Irani, 2015; Rosenblat 2018; Ravenelle 2019; Schor, 2021; Manriquez, 2019). Embedded within the drivers' interface with the app are design features that encourage workers to work at specific times. A *New York Times* article, "How Uber Uses Psychological Tricks to Push Its Drivers' Buttons," describes how Uber uses behavioral science to influence when, where, and how long drivers work by incorporating videogame techniques, graphics, and non-cash incentives (such as encouraging drivers to stay on longer just as they are trying to log out with notices to beat yesterday's earnings) (Scheiber, 2017). (See also Rosenblat, 2018). On another closed labor platform, Instacart, shoppers report that the app design makes them feel like they are playing "Supermarket Sweep" each time they work which, in turn, can

encourage individuals to work longer than intended as they are deeply absorbed in the game of work (Cameron, Chan, & Anteby, 2022). Gamification can encourage deep absorption into the work, leading workers to accept consecutive rides and to strive for hiring ratings at the expense of their own earnings or physical well-being. In my research, I found drivers would skip meals and going to the bathroom to keep driving (Cameron, 2024).

67. *Workplace Games.* Unlike gamification, which relies on rules designed by management to improve workers' affective experience and boost productivity (e.g., Deterding et al. 2011; Mollick & Rothbard, 2014), workplace games are a result of organic interactions between workers and touchpoints in their environment. Said differently, workplace games are the result of spontaneous interactions between co-workers, that reinforce workers' perceptions of status or skill in or at their work, and these games, which often align with organizational objectives, reinforce organizational control. From my study of ride-hailing drivers, I find that workers typically play one of two games — the relational game or the efficiency game (Cameron, 2022). In the *relational game*, workers craft positive customer service encounters, offering gifts and extra services, for example, in the pursuit of high customer ratings. In the *efficiency game*, workers set boundaries with customers, minimizing any extra behavior, in the pursuit of maximizing money per time spent working. These games can make work more meaningful and rewarding to individuals.

68. Elements of uncertainty in the game (e.g., fluctuating pay rates, unpredictable customers) can heighten workers' interest in these workplace games, making it more appealing for them and thus further increasing their work investment as they try to align their own behaviors to the goals of the organization. However, these workplace games and the worker's belief that they are "winning" the game, obfuscates how an organization can nonetheless exercise organizational control over its workers since the terms of "winning" are set by the organization. Indeed, the algorithmic management system and design elements of the user interface can reinforce drivers' games and encourage the playing of one game, that is more tightly coupled with organizational

control, over another. For example, nudges encourage the relational game (e.g., badges, rating systems) and discourages the efficiency game (e.g., incomplete ways to track time spent on app versus money earned) so that workers are more likely to behave in ways that are in alignment with the organization's objectives (Cameron, 2022).

69. In summary, these three practices—constant and confined choice, gamification, and workplace games—can provide workers with a sense of autonomy. However, this autonomy is largely inconsequential because it is artfully doled out by the algorithmic management system as a form of organizational control. In other words, while individuals may feel that they have choice surrounding their work activities, this choice is meted out by Uber's algorithmic management system as a way for workers to have limited choices in a system that was ultimately designed and controlled by Uber.

VIII. Narratives that Ride-Hailing and On-Demand Organizations Use to Influence Workers

A. Cultural Narratives that Ride-Hailing and Other On-Demand Organizations Drawn Upon to Influence Workers

70. In addition to algorithmic management, on-demand organizations draw on socio-cultural narratives on entrepreneurship and hustle culture, glamorizing on-demand work. Called possessive individualism, in this narrative individuals' own positions and actions are emphasized; this emphasis attenuates individuals' relationships to one another, the state, and the common good (Macpherson, 1962). Said differently, when individuals understand themselves as masters of their own fate, they are less critical of other forces, such as organizations and the state, that may play a role in their circumstances (Burawoy, 1985).

71. When on-demand organizations encourage workers to think of themselves and other workers as entrepreneurs, possessive individualism is heightened. Entrepreneurship or

small business ownership is a deeply lauded American value (Streeter, 2015). Indeed, many drivers aspire to be entrepreneurs. And on-demand companies draw on the "romance of entrepreneurism" (Ravenelle 2017: 281) to incentive workers (cf., Levy, 2023 for a similar example of the shift of truck drivers from employees to entrepreneurial owner-operators). In ride-hailing workers are explicitly told by on-demand organizations that they are *not* organizational members, and instead are called "entrepreneurs," "co-creators," "consumers," "service providers" or "partners" (Ravenelle, 2019). The term "Uberpreneur" has appeared in *Forbes* business magazine (Youshaei, 2015). Uber has a series of video vignettes on "Uber Entrepreneurs," who are both entrepreneurial by driving and also using their driving income to support other entrepreneurial "passions."[5] And advertisements from these company reinforce these narratives, telling workers to "Ditch the 9 – 5" and "Be Your Own Boss", implying that workers are entrepreneurs and the crafters of their own destinies. Another outcome of workers seeing themselves as entrepreneurs is that it limits their ability to coordinate with one another, for any type of collective action, because they see themselves as competitors trying to outdo one another (Chai & Scully, 2020).

72. The moralization, normalization, and heroization of long hours, being available, and "doing" is a part of the image of being an "ideal worker" (Cameron, Thomason & Conzon, 2021; Goffman, 1963; Reid, 2015). In popular media, this is often described as "hustle culture", in that there is more to strive for: more money to make, a bigger title or promotion to secure and a higher ceiling to smash through (Hill, 2020). Referencing hustle culture and on-demand work, a *New Yorker* article titled, "The Gig Economy Celebrates Working Yourself to Death," describes the promotional materials directed to the workers of Fiverr, a freelance labor platform that glorifies a culture of overwork and sleep deprivation: "One ad, prominently displayed on some New York City subway cars, features a woman staring at the camera with a look of blank determination. 'You eat a coffee for lunch,' the ad proclaims. 'You follow through on your follow through. Sleep

[5] Examples of "Uberprenreurs" videos: https://www.youtube.com/watch?v=Tls9oV4WmFI
https://www.youtube.com/watch?v=udQNv6DzGxI
https://www.youtube.com/watch?v=Eiq68uYHGOA
https://www.youtube.com/watch?v=hOFFCiJR2Us

deprivation is your drug of choice. You might be a doer.' In one video, a peppy female voice-over urges 'doers' to 'always be available,' to think about beating 'the trust-fund kids,' and to pitch themselves to everyone they see, including their dentist" (Tolentino, 2017).

73. Similar morally laden messaging was targeted at potential on-demand workers during the height of the COVID-19 pandemic to encourage them to sign up on the app and work long hours.[6] Instacart advertisements, for example, called individuals essential workers and went as far to describe them as "heroes" because of their ability to get the right type of cheese for customers (Cameron, Chan, and Anteby, 2022). And on the labor platform TaskRabbit, workers even hid their risk preferences (e.g., hiding the fact they were wearing masks) to be eligible for more jobs on the platform and maintain their high customer ratings (Cameron, Thomason & Conzon, 2021).

74. Uber has often called drivers exalted and heroes, even before the COVID-19 pandemic (e.g., UBER-MDL3084-000012771 ("Here's to heroes like you…"); UBER000192116 ("These are the heroes of the city and of the asphalt…"; UBER_JCCP_MDL_002308529). During the height of the pandemic, for example, there were murals, portraits of drivers on TV and print, emails, and cash rewards that lionize drivers as "everyday giants" (UBER_JCCP_MDL_002308529). Uber also called drivers individually, complimentary upgraded individuals to Uber Pro, created signs, send personalized thank you emails, created a drivers portrait series (UBER_JCCP_MDL_001464695). These items were done independently and in conjunction with various third-party partners such as Next-door (UBER_JCCP_MDL_001464695).

75. Uber emphasizes that by driving workers are serving their community. In a message to drivers Uber said, "Each time you reach a milestone, it represents all that you've

[6] See ride-hailing videos: (1) Thank You Kristin: https://www.youtube.com/watch?v=1m2KPtDYQ0s; (2) Thank You to All Drivers & Delivery People: https://www.youtube.com/watch?v=wOMrfZRrRq4.

accomplished and contributed to your city. You're on a roll and well on your way to reaching even more milestones" (UBER-MDL3084-000000722). Similarly, another message from Uber states, "Here, you're the boss… Driving with Uber gives you the opportunity to get paid weekly… all the while fundamentally changing the way people move around your city. We are looking forward to working with you to help serve" (UBER-MDL3084-000000722). By further example, "Thanks for helping your community ring in the new year safely." (UBER-MDL3084-000000722). Similarly, drivers are described as part of the "Uber family" (UBER-MDL3084-000000722). All of these examples are demonstrative of prosocial motivation, an orientation that generally keeps individuals engaged and continuing to invest in their work (Bolino and Grant, 2016).

76. The schedule flexibility afforded by on-demand work can help support the idea that drivers may see themselves are entrepreneurs, hustling on their own terms (c.f., Occhiuto, 2017 for a similar argument about how schedule flexibility allowed taxi drivers to see themselves as "family men"). Yet many scholars have argued that because many workers are financially dependent on the work, their schedules are determined by when there is peak demand and not truly discretionary (e.g., Ravenelle, 2018; Rosenblat, 2018; Schor et al., 2020; Shevruck et al., 2018). Indeed, algorithmically managed incentives and nudges are designed in such a way to strongly encourage workers to drive at times that are most valuable to the platform organization. Incentives are algorithmically set a price that drivers will not refuse based on extensive data about individual driver's behavior, described as "algorithmic wage discrimination" (Dubal, 2023). Referencing the impossibility of have true schedule flexibility in a job structured by customer demands, James Parrott, the director of economic and fiscal policy at the Center for NYC Affairs at the New School, stated: "It's a fiction that the workers really have flexibility?" (Hu, 2022). Following this logic, workers' schedule flexibility is flexibility in name only as individuals must work specific hours to earn a living.

77. The concept that individuals can multi-home, or work for multiple platform companies simultaneously, has also supported the idea that they are entrepreneurs. Yet multiple

platform companies do not exist in every market and, even when they do, scholars have pointed out that often drivers do not log into multiple apps at the same time (Parrot & Reich, 2024; Parrot, Reich & Yang, 2024).

78. Logging into an app for an on-demand platform signals different things in open-labor and closed-labor platforms. In open-labor platforms, it is possible for individuals to post their profiles on two different platforms for potential work and complete multiple different project-based assignments for the same or different customers. While posting a profile signals that individuals are ready to work, in that they are open to beginning negotiation with customers about a potential project. Individuals may also post their profile and log into the site simply to browse. In both cases, this is distinct from when individuals log into the app for a closed-labor platform; here, the log-in signals that individuals are ready to work immediately (i.e., car or delivery vehicle ready) and without negotiation with a customer. In closed-labor platforms individuals log in during P1 time (i.e., logged on, but not having accepted a match) which is unpaid in most states. Unlike in open-labor platforms, in closed-labor market platforms individuals can only accept one task (a ride in the case ride-hailing) and must log out of the other app while completing the tasks.

79. Moreover, in both open-labor and closed-labor markets, individuals being logged into multiple platform company's apps simultaneously is beneficial for the platform organization since it indicates there are more individuals available to be matched on the platform (e.g., Uber/Lyft displaying maps with more drivers available; Upwork advertising the number of freelancers available on its service). The benefit of having a visibly ready "on-demand" workforce is more valuable for closed-labor market platforms such as Uber and Lyft which match workers and customers in real-time.

80. Historically, platform organizations have used information that indicated individuals were active on multiple apps to send targeted incentives that encouraged commitment to their platform (e.g., Uber's Hell program; Isaac, 2018; O'Brein and Besinger, 2017; Shu, 2017).

In ride-hailing, geofences limit the geographic range of drivers in that they may be confined to do pick-ups in a specific state or a few neighboring regions (e.g., driver in Washington, DC can also do pick-ups and drop-offs in Maryland and Virginia (Isaac, 2018; Rosenblat, 2018; Cameron, 2024).

81. Cultural narratives are sticky, providing insights into why individuals behave in ways that are not always in alignment with their own interests. For example, cultural narratives around autonomy and self-reliance explain why those in agricultural-based occupations (e.g., farming) support and vote for policies that undermine environmental protections for the very land that they depend on for the economic livelihoods (Hoschild, 2019). Narratives around entrepreneurship and hustle culture obscure exploitative elements of on-demand work because workers can imagine themselves as having more autonomy and choice than they may have. Noting the distinct pleasure that comes from embracing these seemingly empowering narratives, McMillan-Cottom (2020: 446) writes, “Knowing the extractive terms of their labor does not diminish [workers] enjoyment of the job. Platform capitalism owes much of its dominance to how good it feels to be captured by the platform.” In summary, broader cultural narratives that are supported and endorsed by on-demand organizations are one of the reasons that make this work so sticky, and it is less likely that workers can realize and vocalize the extent to which their actions fall under organizational control and are being guided and controlled by algorithmic management systems.

IX. How Uber Uses Algorithmic Management to Exercise Organizational Control Over their Workers and Influence their Customers

A. Uber as the Quintessential On-Demand Organization

82. Uber is the quintessential on-demand organization. Financiered by a speculative form of capital, venture capital funding, Uber initially used this financing to subsidize their services to attract more riders and drivers (Rosenblat, 2018; Issaac, 2018). To build up

demand on the system, customers encountered little friction when signing up for services (UBER-MDL3084-000014742) and Uber described itself as customer-centric (e.g. UBER000206296 (Product improvements redefine Uber as customer-centric); UBER-MDL3084-000081772 (Program Lead Planning Summit includes strategic priorities including developing workforce to help drive a customer-centric culture). Drivers are given incentives and referral bonuses to sign up (UBER-MDL3084-000047458). In the hiring process, Uber provides information to help drivers get incidents and tickets removed from their records, making them able to on-board more drivers (UBER_JCCP_MDL_000875369). Another way platforms try to secure market dominance is that on-demand companies try to make their platforms as easy to use as possible for customers. There are minimal standards and verification practices for customer sign-up, with customers often only needing a working credit card.

83. Uber growth in drivers and customers resembles that of a company with explosive ‘hockey-stick’ growth (UBER_JCCP_MDL_003626900). Uber has provided money for driver referrals and customers to increase and subsidize demand. As described in the earlier section, the working conditions of platforms deteriorate as the platform described. [redacted] And, among those that use multiple apps, trust remains a competitive weakness for Uber.

B. The Usage of General and Detailed Control by Uber by its Algorithmic Management System

84. How Uber segments driver's work as follows: P0 – when a driver is not logged into the app, P1 – when a driver is online waiting for a ride request, P2 – when a driver has received and accepted a trip request and is driving to pick-up, and P3 – when a driver is with a passenger driving towards their drop-off location. In various ways, Uber's algorithmic management seeks to manage and control workers in each stage of the work.

85. Uber deploys general and detailed control through their algorithmic management systems. In this section, I describe five different components of their algorithmic management system – matching, upfront pricing, loyalty programs, incentives, and geo-tracking—that together create a comprehensive or "tight" system of organizational control system. Elements of general control are generally outlined in the community guidelines, deactivation policies, terms of service, loyalty program guidelines and driver addendum which lay out the terms that drivers must meet to maintain their good standing with the ride-hailing company.

86. Detailed control is more extensive in that it involves how the ride-hailing companies' algorithmic management systems shape drivers' everyday interactions. Detailed control refers to organizational control over the execution of the work itself, including the pace of work, allocation of tasks, performance evaluations, and discipline. I will describe the mechanics of a driver completing a ride (Rosenblat, 2018; Cameron, 2024), which, at this level of generality, is virtually identical for both companies. Drivers begin to work by first choosing a location to open their app and swiping right to go "on-line." A complete ride consists of 1) the app matching the driver and rider; 2) the driver accepting the ride; 3) the driver getting the rider's location, driving to the rider's location, and waiting for the rider to enter the vehicle; 4) the driver swiping "start ride" on the app and entering the destination on the app; 5) the driver and rider interacting; 6) the driver dropping the rider off; and 7) the driver swiping "end ride" and both the driver and the rider being prompted to rate the other (however, only drivers are required to rate the ride before being matched again). Rides may end prematurely, such as when a rider fails to show up or the app malfunctions. If not matched to another ride before a trip is

complete, then at the end of a ride drivers may stay "on-line" and wait to be matched again or go "off-line" and stop working.

87. Algorithmic management systems exercise detailed control over workers by 1) matching them to riders; 2) determining the price of the ride; 3) guiding the pace of their work (e.g., determining when the next ride is added to the queue for shared rides); and 4) evaluating performance through computing an overall average of customer ratings (Cameron, 2024). In a typical period of driving a driver may only complete a dozen rides but will have more than a hundred unique interactions with the algorithm (Cameron, 2024). Each of these unique human-algorithm interactions is a site of constrained choice in that workers have limited choices available to them to remain in good standing with the on-demand organization (Cameron, 2024). Thus, while drivers do have some schedule flexibility in determining the times and location in which they begin working, once they begin working their choices are constant yet constrained in that they must follow the algorithm's directives and nudges to remain active on the app and earn money.

88. *Uber's Matching Algorithm.* In the P1 period, Uber relies on blind algorithmic matching in which the algorithm matches drivers to riders on a series of factors that are not visible to the rider or driver (but are known to the company itself). As a result, workers state they do not know if they are receiving the "best" ride or perhaps if they are being punished by the algorithmic management system for some reason outside of their personal control (Cameron, 2022). Historically, drivers did not have any control over what rides they are assigned, where they are going, and the duration of their trip. Recent changes have given drivers more discretion in matching, but as explained below the parameters of this choice are still governed by the companies' matching algorithms.

a. Uber created the matching algorithm that links drivers and riders and makes improvement to the algorithm as needed. Inputs into the matching algorithm include rider pickup location and destination, the product riders have selected, driver location, and the drivers in the area. Uber's matching algorithm optimizes

for the best decision for the network, a process that can include forward dispatching or offering rides to drivers before they have completed an in-progress trip.

b. In Trip Radar, drivers may be provided with multiple fares to choose between, with Uber providing drivers with some information about the ride up-front such as an estimated fare, the approximate length of the ride, and/or destination (UBER-MDL3084-BW-00034324; UBER_JCCP_MDL_000532360). Uber has the ultimate discretion regarding which trips are surfaced on Trip Radar and the number of trips presented to the driver.

c. [redacted]

d. Ultimately, while deciding between one or more fares does offer workers some choice these choices are from a limited option set that is defined and controlled by Uber. When Uber drivers are presented a match, they only have a short period to time to make a choice about whether to accept the ride (UBER000178305 (spreadsheet) – at cell D80 in "2021 Local Ops – Rides": "I am incentivized to automatically accept a ride because the notification does not last long. This short window does not leave me with enough time to properly evaluate whether the trip is worth it to me, so sometimes I am stuck with trips I wouldn't have accepted. Extending the acceptance timer for requests mid-trip would help keep rides safer"; UBER_JCCP_MDL_001115639 (spreadsheet) – at cell E1265 in "Kirby Upload Test": "uber isn't concerned with driver safety, had a rider with me on the way to the drop off point, doing 70 on the freeway, get a notification of a new ride, only get 7 secs to accept the new ride, and if i let that lapse, that goes against me and lowers my acceptance rate, I think that's dangerous for the driver"; Cameron, 2024). As already described, this example highlights the constant, if constrained, choices that drivers have in conducting their work.

e. Drivers are limited in the number of trips to a destination or arrival times they can set per day (UBER-MDL3084-00000695).

89. *Upfront Ride Pricing.* Historically, Uber determined driver earnings via a rate card: Uber charged riders a fare based on time and distance set by a rate card, drivers then earned an amount based on the percentage of the rider fare, and Uber took a commission based on the entire fare charged to the rider (Rosenblat, 2018; Isaac, 2017). By 2018, however, both companies began decoupling driver earnings from rider fares by offering upfront pricing for rider fares, first in major metropolitan areas. The switch from rate cards to upfront pricing for rider fares introduces more opacity into the system in that riders were quoted a separate fare amount before the ride occurred, and drivers were no longer explicitly paid based on the amount charged to the rider (Rosenblat, 2018). Historically, drivers had a sense of how much they would earn for a ride, given the location, day, and time, and could project their earnings and get a sense of when the algorithm was acting unpredictably (i.e., not properly accounting for incentives a driver was entitled to; Cameron, 2022). However, in 2022 Uber introduced upfront pay for drivers. Under this structure, rather than setting rates per mile and minute, driver earnings are algorithmically determined by Uber, presented to the driver before the trip begins, and based on a combination of factors which are not fully disclosed to the drivers. For Uber, upfront driver pay is designed to nudge workers to behave in a certain way, such as working at a certain time or location, that is in alignment with the organization's interest of having a sufficient pool of drivers available and ready to work to meet customer demand. This algorithmic opacity leaves drivers with even less insight into how key decisions are made about their work and more easily allows their actions to be even more easily shaped by Uber's algorithmic management system.

a. *Uber's Real-Time Upfront Pricing.* In upfront pricing, Uber sets driver fares up-front, during P1, based on marketplace dynamics that are specific to a particular place and a particular time. These driver fares are presented to the driver before they accept or decline the ride. Driver fares are based on a base rate on estimated time (per-minute rate), distance (per-mile rate) of a trip, distance to the rider pick-up location, real-time demand incentives and surges), tolls, surcharges,

governmental service fees and Uber-derived service fees. Surges (i.e., real-time algorithmically calculated demand incentives) are embedded into the fare calculation and can fluctuate due to market-based demand (UBER-MDL3084-00000659). Drivers do not have the ability to influence the driver fare amount presented to them. And significantly, when drivers accept these rides, they are unable to see what the rider is being charged or the inputs that make-up the that amount.

b. [redacted] And while Uber, per se, may not specifically set the surge amount or other specific details for each ride, Uber and its employees do retain unilateral control over the ride pricing, write the software code, and determine the inputs and outputs of the real-time dynamic pricing system. Algorithms designed by Uber set the base rate based on variable situational factors.

c. In summary, the upfront pricing that is part of Uber's algorithmic management system enables greater organizational control by Uber over drivers. By making pricing for driver pay opaque, Uber can more easily direct workers to take the rides that it desires them to take without drivers knowing how much Uber is earning from each ride. This is because while drivers can see some input into the fare calculation after the competition of the ride, they do not have insights into the rider price or variable fees, both of which are set by Uber. Further highlighting the opacity of the algorithmic management system, drivers do not have this information available to them at the time they must decide whether to accept a ride request. In summary, when Uber optimizes the amount of driver pay for market efficiency which may or may not be the worker's best interest.

90. *Loyalty Programs.* While upfront pricing allows Uber to optimize for short-term demand/supply of riders and customers, the goals of Uber's loyalty programs and

planned incentives are two-fold: to encourage drivers to work in the short-term, at peak demand, and long-term retention. In other words, these loyalty programs and planned incentives aim to control drivers' behavior by keeping them working on the platform for a longer tenure affecting driver's behavior during P0. Programs such as Uber Pro link workers' behaviors (e.g., ratings) to incentives that drivers value (e.g., priority access to ride, gas discounts). Unlike consumer loyalty programs, such as an airline rewards program, these programs affect workers' granular interactions with the work itself and workers' economic livelihood. For example, by keeping their customer rating above threshold, drivers may get additional information about their ride such as the destination address before accepting (historically) or access to priority rides at the airport (currently). To maintain this benefit, however, the drivers are required to keep their ratings high (UBER_JCCP_MDL_000084271: "Uber Pro is our way of rewarding drivers . . . with a rating of 4.85 or higher and a cancellation rate lower than 4%"). These strategies reinforce the notion that workers have autonomy, while the companies' algorithmic management systems are operating in ways that increase organizational control over the workers and consolidate power in the hands of the two companies.

91. On-demand companies rely on workers being available to work whenever needed during P1. However, a crucial issue for these companies is driver churn – with some research suggesting as a high as an 80% churn rate in the first six-twelve months (Rosenblat, 2018; Katz & Krueger, 2018). Loyalty programs are designed to address this problem by encouraging driver commitment and loyalty (i.e., in P0 times) as well as trying to shape driver's in-app behavior during P1.

92. A general finding across on-demand companies is that most of the work on these platforms, especially the most highly valued work (i.e., work at high-demand times), is done by a minority of drivers (Pareto's principle, 80/20 rule; Koch, 1999; Gray & Suri, 2019). Securing high-quality committed drivers is crucial to these companies' business models, as a disproportionate amount of their revenue is dependent on a minority number of workers. This principle applies to drivers at Uber. Correspondingly, loyalty programs, such as Uber Pro, as well as individualized planned incentives, are all aimed

at encouraging driver commitment and retention for their most highly valued drivers. In the following sections, I describe the loyalty programs and planned incentives designed by Uber, deployed by their algorithmic management system, and how they are used to influence and direct workers' behaviors.

a. *Uber's Loyalty Program, UberPro:* Offering great customer service, as indicated by higher customer ratings, and a workforce with a longer-term tenure can contribute positively to Uber's bottom line. Knowing that only a small percentage of their drivers are the highest value, loyalty programs such as Uber Pro are designed to retain the highest value drivers. [redacted]

b. [redacted] More generally the rewards program rewards drivers who put in the most hours.

a. [redacted]

b. Given the importance of this small segment of long-term drivers, Uber has invested considerable efforts in putting together a team to design programs and planned incentives that encourages drivers to remain committed to the Uber platform [redacted] Moreover, many of the perks provided by Uber Pro, which are earned through points, directly benefit drivers by helping them ensure their cars are running smoothly (e.g., roadside assistance, priority phone supports discounts on car maintenance), something that, in turn, benefits Uber. The goals that are built-into loyalty programs are to keep drivers on the road longer and offer high quality (and rated) customer service. Overall, by ensuring that UberPro directly affects drivers' satisfaction, it can keep drivers motivated to work longer [redacted]

c. [redacted]

93. *Incentives.* Incentives have two goals: volume and shaping. [redacted]. Real-time incentives aim to synchronize drivers' work hours with customer demands. Planned incentives are another feature of Uber's algorithmic management system that enables organizational

control over drivers. The goal of planned incentives is to induce drivers to work for longer hours, often at the times preferred by Uber, and to continue working for Uber over the long-term. Planned incentives are another way to manage and control workers' behavior in P0 times. Drivers are required to meet several of Uber's benchmarks – such as acceptance a certain percentage of rides or completing a certain number of rides per hour, to be eligible for these incentives (UBER_JCCP_MDL_000875766; UBER_JCCP_MDL_000605376; UBER_JCCP_MDL_000584015).

a. *Uber's Planned Incentives.* Uber uses planned incentives to influence and shape driver behavior. Examples of planned incentives include DxGy (Do X and Get Y), Quest, lotteries/sweepstakes, hourly guarantees, and offering rewards if drivers work at peak hours or complete a certain number of consecutive rides (UBER_JCCP_MDL_000875766, 5850-4, UBER-MDL3084-000009784; UBER-MDL3084-000012512; UBER-MDL3084-000000722; UBER_JCCP_MDL_000605376 "You must accept 90% of your trips to qualify for the guarantee…" Trips per hour calculation; UBER-MDL3084-000000722 at 935). Drivers are personally targeted with these incentives (UBER_JCCP_MDL_000584033), especially new drivers (UBER_JCCP_MDL_000202426).

b. *Uber's Real-time Incentives.* Uber sends messages to drivers to encourage them to driver at peak times, such as music festivals, car shows or sporting events, and can also offer incentives for driving at these times given certain requirements (e.g. acceptance rate) are met (UBER_JCCP_MDL_000584033; UBER-MDL3084-000000722; *See generally* UBER_JCCP_MDL_000202426; UBER_JCCP_MDL_000584015: Promo for Chicago area; "Guarantee hours are Saturday, July 25th 10PM-4AM at $23/HR in gross fares and Sunday July 26th 9AM-5PM at $22/HR in gross fares…How to Qualify 1. Accept at least 90% of trip requests 2. Complete at least 1.5 trips per hour online (on average) 3. Be online for a minimum of 2 hours (per guarantee period) to qualify for that time block" UBER_JCCP_MDL_000584033: Promo for Charlotte area. Includes

"SPECIAL INVENTIVES FOR PNC MUSIC PAVILION PICK-UPS" from "Friday, August: 7th 10pm - 12am (midnight)" and "Sunday, August 9th: 10pm - 12am (midnight)"; encourages drivers to sign-on during "busy hours" including "Friday Night 7pm-3am" and "Saturday Night 7pm-3am"; notes "All Weekend - Alpha Phi Alpha Conference - Bars & Clubs in Uptown - Look for increased late night demand" UBER_JCCP_MDL_000605376: Promo for Tulsa area. Guarantees $20 gross fare per hour when making 2 minimum trips per hour when driving late at night; "you must accept 90% of your trips to qualify for the guarantee"). Uber encourages drivers to travel to different cities to work during busy events (UBER-MDL3084-000000722).

c. *Other Nonmonetary Incentives*. Other incentives include promotion and contests, some notification messages which are pushed directly to drivers (e.g., free tickets to basketball games; UBER-MDL3084-000000722; UBER000169934).

d. Uber tries to create positive interactions/affinity between themselves and their workforce. Through their moment of joy campaigns, they describe giving status markers (MVP) or ice cream to drivers as well as organizing activities around cultural events (UBER-MDL3084-000008700).

e. As already described, gamifying elements of work can inspire individuals to work longer and harder than they would otherwise. Uber provides recognition of drivers who meet and/or exceed the quotas they provide, such as matching tips or non-monetary awards (UBER_JCCP_MDL_000172834). Further, Uber purposefully designs aspects of the work as a game, letting drivers build their own incentive structures (UBER000184830).

94. *Importance of UberPro, Planned, and Realtime Incentives in Addressing Driver Churn*

a. [redacted]

[redacted]

b. [redacted]

c. As already described, workplaces gamification encourages drivers to work and increase their on-app engagement (i.e., driving). Below, I provide examples of gamification for each of the five bellwether cases.

i. Jeffery Richardson received numerous Quest notifications encouraging them to drive longer to receive benefits such as cash back on gas (UBER-MDL3084-BW-00000011; "You're just one step away. You're so close to Cash Back Now that you have your card, just tap below to start earning Cash Back from your everyday spending on gas, groceries, auto care, and more at participating merchants."

ii. Hassan Turay received numerous Quest notifications encouraging them complete a certain number of rides (UBER-MDL3084-BW-00000015; "Earn up to an extra $275 with Quest Phoenix | 9/23 - 9/26 You can unlock extra earnings this weekend", "You can drive and earn up to $190 extra. Select your Quest before 11:59pm on Sunday"). They received congratulatory messages when they completed a Quest (UBER-MDL3084-BW-00000015; "Hassan

you mastered your Quest!"; "You achieved your Quest reward extra earnings are yours!"), reached certain milestones (UBER-MDL3084-BW-00000015; "You've reached your next milestones!") and as their status increased and their (UBER-MDL3084-BW-00000015, "Hassan, Gold status is yours!") and rating improved (UBER-MDL3084-BW-00000015; "Your Uber rating is improving!"). They also received messages encouraging them to drive more to achieve higher status levels (UBER-MDL3084-BW-00000015; "This Diamond status has your name on it."). Taken together, these notifications and features within the app encouraged Hassan Turay to increase their on-app engagement and work longer.

iii. Driver, Edwin Orozco, received numerous Quest notifications encouraging them complete a certain number of rides (UBER-MDL3084-BW-00000022; "Choose your Quest before 11:59pm on Thursday", "You can drive and earn up to $115 extra this weekend. Select your Quest before 11:59pm on Thursday.", "Earn up to an extra $225 with Quest San Francisco Bay Area | 9/16 - 9/19 You can unlock extra earnings this weekend Find out more Select a Quest before setting out You could earn extra this weekend."). They received congratulatory messages when they reached certain ride milestones (UBER- UBER-MDL3084-BW-00000022; "You're really tackling these trips! Here's to 40 trips You're accomplishing big things, Edwin. Make room for even more driving milestones." Taken together, these notifications and features within the app encouraged Edwin Orozco to increase their on-app engagement and work longer

iv. Felix Rodriguez received numerous Quest notifications encouraging them complete a certain number of rides (UBER-MDL3084-BW-00000029); "Choose your Quest before 11:59pm on Sunday; "Uber: This week, your Quest is an extra $55 for completing 55 trips"). They received congratulatory messages when they completed a Quest (UBER-MDL3084-BW-00000029; "You achieved your Quest reward extra earnings are yours!", as their status

increased UBER-MDL3084-BW-00000029, "Check out your status and rewards. An Uber Pro period starts today (You've got Diamond status. You've reached the top Uber Pro status! Check out your rewards in the app. See your rewards See your rewards."), and ratings improved (UBER-MDL3084-BW-00000029; "Your rating is improving. You've made some big improvements, and your hard work shows. Your average star rating is increasing. Keep it up to stay active on the Uber app." They also received reminders of the benefits of their status (UBER-MDL3084-BW-00000029, "Your Uber Pro Diamond status makes it easy. Felix, file your taxes for free As a driver with Uber Pro Diamond status, you can file both your state and federal taxes for free with TurboTax Self-Employed, the online tax service for independent business owners and freelancers.") Taken together, these notifications and features within the app encouraged Felix Rodriguez to increase their on-app engagement and work longer.

v. Michael Le received numerous Quest notifications encouraging them complete a certain number of rides (UBER-MDL3084-BW-00000032; "Choose your Quest before 11:59pm on Thursday.", "Choose your Quest for 3/17 - 3/20"). They received congratulatory messages when they completed a Quest (UBER-MDL3084-BW-00000032; "You achieved your Quest reward—extra earnings are yours!", "Michael you mastered your Quest 🙌" "You achieved your Quest reward extra earnings are yours!"), reached certain milestones (UBER-MDL3084-BW-00000032; "Congrats on hitting a new milestone! You have 4000 5-star ratings.", "You're in triple digits! Take time to celebrate.", "Michael, you've completed 9,000 trips 😍", "Wow, Michael! You've hit another 5-star rating milestone ☆") as well as encouraging notes ("You're almost there ✨"). They also received messages reminding them to the check their status and reminders about their status benefits (Head to the app to check your status", "Shift to gift mode with Uber Pro rewards 🎁", Accomplish almost anything with Uber Pro rewards ✅"). Taken together,

these notifications and features within the app encouraged Michael Le to increase their on-app engagement and work longer.

d. In summary, the planned incentives that are designed and maintained by Uber's algorithmic management system enable Uber to have greater organizational control over drivers. These incentives are individually tailored to drivers, enticing them to work at the periods of time and places that Uber desires. More broadly, the incentives are designed in such a way to increase drivers' job satisfaction and earnings experience such that they remain working for Uber.

95. *Uber's Algorithmically Mediated Customer Ratings System*. Uber's algorithmically mediated customer rating systems allow the companies to launder their organizational control through customers. This allows customers to control workers' behaviors through the rating system, but power remains with the platform organization. The five star rating system sets expectations for how drivers are supposed to behave (i.e., service rules; UBER_JCCP_MDL_003300332; UBER-MDL3084-000014618; #11300.1; #11315.1). Customers are prompted to rate drivers after every ride and drivers who receive poorer ratings face sanctions.[7] Moreover, drivers have limited means at their disposal to refute ratings they deem were unfairly given by customers. To ensure consistent service encounters, Uber curates the customer-worker interactions through prescribing "service rules" about what specific emotions to display and behaviors to engage in that are then evaluated by the customer (UBER_JCCP_MDL_000016203: "one thing we might consider is training some drivers in 'proactive positive culture change' strategies…"). As already described, many of these service rules can be viewed in Uber's videos and email-communications to drivers. Uber allows workers to opt-into WhatsApp messaging so they can reach drivers even more instantaneously (UBER_JCCP_MDL_000876347). Ensuring drivers deliver good customer service is important for the companies' business models because satisfied customers will continue using the service. To ensure that drivers behave accordingly, the customer ratings

[7] At the same time, workers on platforms may have artificially high ratings (Rosenblat, 2018; Rahman, 2021, 2024). Most customers give a five-star rating, knowing that anything less may harm the workers' future work opportunities. On Uber, ratings are based on a drivers' last five hundred rides (UBER-MDL3084-000000681).

systems evaluate driver's behaviors, with drivers with poor ratings facing sanctions and possible deactivation from the platform.

a. *Uber's Customer Ratings and Related Warnings, Suspensions, and Deactivations.* Uber issues warnings to and deactivates drivers with a rating lower than a city-specific threshold; however, this threshold number is not shared with drivers (UBER-MDL3084-000000621). However, while drivers are held accountable to keeping an overall customer rating, they are unaware of the specific rating they receive from each customer (UBER-MDL3084-000000681. "Rider comments are always anonymous. Ratings are confidential, so we can't provide information around the rating of a specific trip"). Overall, it is Uber that designs the rating system (e.g., what the scale is, what is the threshold to remain activated, dimensions on which drivers are rated) and threshold amounts for continued driving which, in turn, controls drivers' behaviors

b. Uber provides tips to drivers about how to provide high quality service and improve their ratings through their learning center, podcasts, videos, emails, and others forms of communication (e.g., open vehicle doors, provide bottled water, snacks, gum, mints, and cell phone chargers", "Help with luggage and bags when it's safe to do so"; how to find busy areas; -UBER_JCCP_MDL_001535251: "Rides Content" includes "Pro Tips: How to be a 5-star driver"; UBER-MDL3084-000014618; UBER_JCCP_MDL_000172834; UBER_JCCP_MDL_000202426). Uber automatically sends learning material to drivers for the first 25 trips (UBER_JCCP_MDL_000876347).

a. Uber tells drivers, "There's magic at every ride, and at the center of that magic is you.…you're at the heart of the Uber experience (UBER-MDL3084-000000722). This "magic" is precisely what is described in the service rules outlined in the podcasts, videos, learning center, and other training materials.

b. Customer ratings and compliments are a point of pride for many drivers and keep drivers motivated and engaged in the work (UBER_JCCP_MDL_000444051: "I definitely agree with the point that drivers care quite a bit about ratings themselves (as a point of pride), rather than as a signal that some other policy is about to be triggered."; #5363.1; Cameron, 2022).

c. Customers ratings are confidential such that drivers do not know which rider rated them (UBER-MDL3084-000000681. "Rider comments are always anonymous. Ratings are confidential, so we can't provide information around the rating of a specific trip.")

d. As described earlier caring about customer ratings, and providing amenities are elements of the relational game in which drivers spend considerable efforts to satisfy customers to "win" the game. Drivers become so vested in the game they do not decline or cancel rides. Altogether, the emotional highs of interacting with customers can keep drivers working and aligning their behaviors to Uber's algorithmically mediated customer ratings system. [redacted]. Indeed, some drivers report that ratings are more important than cash (#5363.1).

e. As described earlier, Uber's algorithmically mediated customer ratings are a way for Uber to launder control through customers. In laundering control through customer ratings, Uber claims that they are not exercising organizational control (because the riders are doing the rating), when it is Uber that has designed the customer rating system, and the thresholds drivers must keep maintaining access. Said differently, Uber has organized the entire system that controls drivers during P0, P1, P2, and P3. Thus, while Uber does not give the actual ratings, it created the system for doing so, prompts riders to give those ratings, and acts against drivers based on the ratings that riders input.

f. *Deactivation and Reactivation.* [redacted] Because of the finality of deactivation, this may make workers more wary about not following Uber's rules and nudges.

g. In some instances, if deactivated, Uber requires drivers to pay for a quality improvement class by a third-party vendor to be considered for re-activation (UBER_JCCP_MDL_000875766). The presence of such classes provides further data to support the claim that Uber has service rules for how drivers are to behave towards customers; failure to follow these rules results in negative consequences for drivers (e.g., being unable to regain access to the app). Regaining access after deactivation is difficult and workers have limited means of recourse to regain access through official channels.

96. [redacted] UBER JCCP MDL 003306684: Uber tested S-RAD (safety risk assessed dispatch) in "shadow mode" in LA in 2018).

97. *Geo-tracking and Other Monitoring of Drivers' Activities.* Another way that Uber's algorithmic management system controls workers is through monitoring their location

while driving. Monitoring and organizational control are closely linked because through location monitoring, Uber can track drivers' location and render penalties for (supposed) non-compliance to rules.

a. [redacted] UBER_JCCP_MDL_000323152: In 2017, Uber identified utilizing "both behavioral and trip level correlates to identify high risk users on our platform" including "Trip level anomaly detection to deter bad behavior (i.e. real time check-ins) by surfacing targeted, friendly messages that make it clear folks are still on the map…For example, 'Hi! We noticed it's taking you longer to get from A to B. We're here to help if needed'" as "high impact" opportunities. An Uber employee stated "we will be building this out more" but it is unclear when these types of motifs were actually built out. #21754.1 [redacted] (UBER_JCCP_MDL_000549109; UBER-MDL3084-000008671; UBER_JCCP_MDL_003306684).

b. Uber can provide a beacon (a light-up device that uses color-pairing technology) so that customers can identify driver's cars (UBER-MDL3084-000008671).

c. Devices such as dash cameras (dashcams) and audio recordings, which can be subsidized by Uber, surveil drivers' behaviors and their data can be used to shape their future work opportunities (UBER_JCCP_MDL_003300332 at 0336; UBER_JCCP_MDL_002702651; UBER_JCCP_MDL_000516118; #11478.1; #11734.1; UBER_JCCP_MDL_000250635; UBER_JCCP_MDL_000453907). Uber notes in an ideal scenario dashcams would be required in every car and there would be automatic video and audio recordings of every ride (UBER_JCCP_MDL_000250635).

98. In conclusion, this report demonstrates that Uber is not a true marketplace because workers are managed and controlled by the platform's algorithmic management system.

Customers do not choose their drivers from a set and, instead, are assigned drivers by the platforms' algorithmic management system. (The same relationship applies to drivers.) In addition, Uber sets the price for a fare and processes payment. Platforms launder control through customers through the five-star rating system, but ultimately power resides with the platform organization.

Lindsey D. Cameron

Lindsey D. Cameron, Ph.D.
October 24, 2025
Sanford, Florida

EXHIBIT A: CURRICULUM VITAE
EXHIBIT B: MATERIALS CONSIDERED
EXHIBIT C: PRIOR TESTIMONY

EXHIBIT A - CURRICULUM VITAE

LINDSEY D. CAMERON

2027 Steinberg- Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104

215.898.0990
ldcamer@wharton.upenn.edu
www.lindseydcameron.com

ACADEMIC APPOINTMENTS

Wharton School, University of Pennsylvania

Assistant Professor in the Department of Management	2019 +
Assistant Professor in the Department of Sociology (by courtesy)	2022 +
Dorinda and Mark Winkelman Distinguished Faculty Scholar	2024 - 2025
Faculty Affiliate, AI at Wharton; People Analytics at Wharton	2023 +
Pre-doctoral Fellow (Funded Visiting Student)	2017 - 2018

Institute for Advanced Study
Fellow (Member), Platforms theme, School of Social Science 2023 - 2024

Berkman Klein Center for Internet and Society, Harvard University
Faculty Affiliate 2023 +

Data and Society Research Institute
Faculty Affiliate 2024 +
Faculty Fellow - Race, Technology, and the Quantified State 2022 - 2023

Ross School of Business, University of Michigan 2015
Lecturer

EDUCATION

University of Michigan, Stephen M. Ross School of Business 2020
Ph.D., Business Administration (Management and Organizations)
Dissertation: *The Rise of Algorithmic Work: Implications for Managerial Control and Worker Autonomy*
Committee: Jerry Davis (Chair), Jane Dutton, Beth Bechky, Seth Carnahan and Tawanna Dillahunt

- Winner, *Likert Dissertation Prize*
- Winner, *Psychology of Technology Dissertation Award*
- Winner, *Industry Studies Dissertation Award*
- Runner-Up, *Louis Pondy Best Dissertation Paper*
- Finalist, *Grigor McClelland Doctoral Dissertation Award*

George Washington University 2009
M.S., Engineering Management, Focus: Crisis, Emergency and Risk Management

Harvard University 2005
S.B., Electrical Engineering and Computer Science; Languages: French, Arabic

PEER-REVIEWED PUBLICATIONS

1. **Cameron, L.**, Mayberry, K. +, & Maffie. M. (Conditionally Accepted*, Industrial Labor Relations Review*)**.** "Voice Activism: How Digital Counterpublics Cultivate Change in the Gig Economy"*.*
+ *Student Author*

- *Best Paper Award* (Labor and Employment Relations Association)

2. **Cameron, L.**, Conzon, V., & Lam, L.+ (Conditionally Accepted, *Research in Organizational Behavior*). "Selling the Self: Neonormative Control and the Platform Paradox."
+ Student Author

3. **Cameron, L.** (2024). "The Making of the "Good Bad" Job: How Algorithmic Management Manufactures Consent through Constant and Confined Choices." *Administrative Science Quarterly, 69(2), 458-514.*
   - *Winner,* Responsible Research in Management Award (AOM Fellows and RRBM selection committee)
   - *Best Published Paper Award* (AOM CTO Division)
   - *Honorable Mention*, Distinguished Scholarly Article Award (ASA LLM Division)
     - Best published paper in past three years
   - *Winner*, Responsible Business Education Research Award for Social Impact (*Financial Times*)
   - *Runner-Up,* Louis Pondy Best Dissertation Paper (AOM OMT Division)
   - *Best Paper Award* (AOM CTO Division, top 10% conference papers)
   - Translated in Chinese for *Management Insights*, the official publication of the International Association for Chinese Management Research.

4. Kulkarni, M., Gehman, J.*, Glaser, V.*, Greenwood, M.*, Islam, G.*, Lindebaum, D.*, Mantere, S.*; Pachidi, S.*, Petriglieri, G.*, **Cameron, L.*,** Rahman, H.*, Vaara, E.* & Van den Broek, E.* (2024). "The Future of Research in an Artificial Intelligence Driven World." *Journal of Management Inquiry, 33(3), 207-229*.
**Shared Authorship*

5. Rahman, H.*, Karunakaran, A.* & **Cameron, L.*** (2024). "Taming Platform Power: Taking Accountability Into Account, An Integrative Review on Digital Platforms." *Academy of Management Annals, 18(1), 251-294*.
**Shared First Authorship*

6. **Cameron, L.*,** Lamars, L.*, Leicht-Deobald, U.*, Lutz, C.*, Meijerink, J* & Mohlmann, M.* (2023). Algorithmic Management: Its Implications for Information Systems Research. *Communications of the Association of Information Systems, 52(21), 518-537*.
**Authorship Alphabetical*

7. **Cameron, L.**, Chan C., & Anteby, M. (2022). "Heroes from Above But Not (Always) From Within? Gig Workers' Responses to the Sudden Public Moralization of their Work." *Organizational Behavior & Human Decision Processes, 172*, *104179*.
   - *Best Symposium Award* (AOM MOC Division)

8. **Cameron, L.** (2022). "'Making Out' While Driving: Relational and Efficiency Games in the Gig Economy". *Organization Science, 33(1), 231-252*.
   - *Best Paper Award* (AOM MOC Division, top 10% conference paper)

9. **Cameron, L.*** & Rahman, H.* (2022). "Expanding the Locus of Resistance: The Co-Constitution of Control and Resistance in the Gig Economy." *Organization Science, 33(1), 38-58*.
**Shared First Authorship*
   - *Best Published Paper Award* (AOM CTO Division)
   - *Industry Studies Association's Giarratani Rising Star Award*
   - *Best Paper Award* (AOM CTO Division, top 10% conference papers)

10. **Cameron, L.,** Thomason, B., & Conzon, V. (2021). "Risky Business: Gig Workers' and the Navigation of Ideal Worker Expectations During the COVID-19 Pandemic". *Journal of Applied Psychology, 106(12), 1821-1833*.

11. Hafenbrack, A.*, **Cameron, L.*,** Spreitzer, G., Zhang, C., Noval, L., & Shaffakat, S. (2020). "Helping Others by Being in the Present Moment: Mindfulness and Prosocial Behavior at Work." *Organizational Behavior and Human Decision Processes, 159(C), 21-38*.

**Shared First Authorship*

12. Kamaswaren, V., **Cameron, L.,** & Dillahunt, T. (2018.) Support for Social and Cultural Capital Development in Real-time Ridesharing Services. *Computer-Human Interactions. CHI 2018: ACM Conference on Human Factors in Computing Systems.* (Paper 342, 12 pages). ACM. [HCI conference proceedings are respected as journal articles within the field]

13. Spreitzer, G.M., **Cameron, L.,** & Garrett, L.E. (2017). Alternative Work Arrangements: Two Images of the New World of Work. *Annual Review of Organizational Psychology and Organizational Behavior, 4(1), 473-499*.

OTHER PEER-REVIEWED PUBLICATIONS AND BOOK CHAPTERS

14. Mayberry, K.+, **Cameron, L.**, & Rahman, H. (2024). *Fighting Against the Algorithm: The Rise of Activism in the Face of Platform Inequality*. In Julie MacLeavy and Frederick Harry Pitts (Eds.), Handbook of the Future of Work. New York: Routledge.
+ *Student Author*

15. **Cameron, L.,** Garrett, L.E, & Spreitzer, G.M. (2019). Contingent, Contract, and Alternative Work Arrangements. *Oxford Bibliographies in Management.* Ed. Ricky Griffin. New York: Oxford University Press

MANUSCRIPTS UNDER REVIEW

16. **Cameron, L.**, Hill, J., Dubal, V., Amrute, S., Weigel, M., Ticona, J., Van Doorn, N., & Aninch, E. (*Revise and Resubmit* Requested, *Journal of Management Inquiry*). "Thinking with and Beyond Labor and Technology: A Theoretical Investigation of How the Ghost Variables of Race, Caste, Gender, Citizenship and Class Shape Gig Work." Revise and Resubmit requested 9 April 2025.

17. **Cameron, L.**, Schor, J., Baretto, I., Vianna, F., Alcadippani da Salveira, R., Bhallamudi, I., Caza, B., Reid, E., Wohl, H., Kyratzi, S., Ravenelle, A., Ghaedipour, F., & Conzon, V. (*Revise and Resubmit* Requested, *Journal of Management Inquiry*). "Thinking with and Beyond Labor and Technology: An Empirical Investigation of How the Ghost Variables of Race, Caste, Gender, Citizenship and Class Shape Gig Work." Revise and Resubmit requested 9 April 2025.

18. Aidinoff, M., Boczkowski P., **Cameron L.,** Kapila K., Kelly A., Krupar, S., Llamas-Rodriguez, J., Nakamura, L., Nelson, A., Nieborg., D., Sandvig, C., Ticona, J., Weigel, M., Wohl, H. & Ziewitz, M. (*Revise and Resubmit* Requested, *Science*). "As We May Think About Platforms: Towards a Platform Manifesto." Revise and resubmit requested 1 November 2024.

19. **Cameron, L.*** & Meuris, J.* (Revise and Resubmit Requested, *PLOS ONE*) "The Perils of Pay Variability: Determinants of Worker Aversion to Variable Compensation in Lower-Wage Jobs." Revision Requested on 3 October 2025.
**Shared First Authorship.*
- *Best Overall Paper Award* (AOM HR Division, top overall conference paper)
- SSRN "Top Paper in Human Resource Management & Organizational Behavior" based on downloads

20. **Cameron, L.*** & Weigel, M.* (Under 2nd Round Review, *Platforms and Society*). The Pitch and the Catch: A Genealogy of Sponsored Entrepreneurship from Amway to Uber. Resubmitted on 1 September 2025.
**Shared First Authorship.*

21. Birced, E.* & **Cameron, L.*** (Under Review, *Organization Science*). Status Striving: The Laundering of Control Through Consumers in the Platform Economy. Submitted on 15 July 2025.
**Shared First Authorship.*

WORKING PAPERS

22. **Cameron, L.** (Working Paper) "Scalable Subjugation: The Myth of Geographic Scalability in Digital Platforms and How People Reconstitute Platforms Globally." *Target: American Sociological Review, Winter 2025*
- *Best Paper Award* (Labor and Employment Relations Association)
- *Best Symposium Award* (AOM MOC Division)

23. **Cameron, L.***, Holm, A.* & Lee, K.* (Working Paper). "Thousands of Flowers Have Bloomed, Now What?: Building a Potager to Study Work." *Target: Organization Science, Winter 2025*
**Shared First Authorship.*

TECHNICAL REPORTS

24. **Cameron, L.** (2025). Expert Witness Report for the Minnesota Attorney General re: Attorney General of Minnesota vs. Shipt, Inc., Fourth Judicial District. (No. 27-CV-22-15991)

25. Aidinoff, M., Boczkowski P., **Cameron L.,** Kapila K., Kelly A., Krupar, S., Llamas-Rodriguez, J., Nakamura, L., Nelson, A., Nieborg., D., Sandvig, C., Ticona, J., Weigel, M., Wohl, H. & Ziewitz, M. (2024). Five Theses on the Gravity of Platforms, *School of Social Science, Institute for Advanced Study (IAS).*

26. **Cameron, L.** (2024). Expert Witness Report for the Massachusetts Attorney General re: Attorney General of Massachusetts vs. Uber Technologies, Inc. and Lyft, Suffolk Superior Ct. (No. 2084CV01519-BLS1)

27. Soujouner, A., Houseman, S., Mueller, C., **Cameron, L.,** Handel, M., Kelly, E., Kemp, J., Kosanovich, K., Kreisman, D., Mas, A., Mueller, A., Pedulla, D., Robertson, C., Rodgers, W., Schenider, D. & Smith, J. (2023)."Employment and Work Arrangements Content Panel Report." *National Opinion Research Center (NORC) at the University of Chicago.*

SELECTED PRACTITIONER PUBLICATIONS

28. **Cameron, L.*,** Ticona, J.* & Wohl, H.* (24 July 2025). The Hidden Dangers of Eliminating Taxes on Tips. *Newsweek.*
**Shared Authorship.*

29. Wohl, H. & **Cameron, L.** (8 Jan 2025). Unlikely Bedfellows: How Platforms Shortchange Porn Performers and Ride-hailing Drivers Alike. *The Conversation.*
- Reprinted by the *Seattle Post*, *San Francisco Chronicle*, *CT Insider*, and *Albany Times*; 10,000+ views

30. **Cameron, L.** & Mayberry, K. (November 2024). What Activism Looks Like in the Gig Work Era. *Labor and Employment Relations Perspectives on Work Magazine.*

31. **Cameron, L.** (21 June 2024). How Micro-Choices and Games Motivate Gig Work. *Harvard Business Review.*

32. Rahman, H., Karunakaran, A. & **Cameron, L.** (4 June 2024). Taming Platform Power: Multi-sided Platforms Need Multi-Sided Accountability. *Platform Papers*, 18(1), 251-294.

33. **Cameron, L.** & Mayberry, K. (3 April 2024). How Gig Work Pits Customers Against Workers. *Harvard Business Review.*

34. **Cameron, L.** Chan, C., & Anteby, M. (1 February 2024). Why Calling Your Workers Heroes May Backfire. *Harvard Business Review.*

35. **Cameron, L.** & Hafenbrack, A. (12 December 2022). Research: When Mindfulness Does — and Doesn't — Help at Work. *Harvard Business Review.*

36. **Cameron, L.** & Winn, B. (2021). Worker Voice & Choice: The Democratization and Uberification of Work. (Linking Theory + Practice Series). *People + Strategy Journal, Society for Human Resource Management.*

37. **Cameron, L.** & Rosenblat, A. (10 August 2020). Gig Work Used to Be a Recession Proof Safety Net. Not Anymore. *Fast Company.*

38. **Cameron, L.** (as interviewed by Cross, M.). (15 November 2019). The New Uber Law's Ripple Effect. *Kiplinger's.*

RESEARCH IN PROGRESS

Eren, D., **Cameron, L.,** & Anteby, M. (Data Collection). Cybersecurity Professionals and Gray Hat Hacking

Kessinger, R., **Cameron, L.,** & Smith, L.+ (Data Collection). Resocialization after Total Institutions
+ *Student Author*

Weigel, M.* & **Cameron, L.*** (Writing). Learning to Labor in the Global Economy: Sponsored Entrepreneurship and the Promise of Portable Infrastructure from Amway to Uber
**Shared Authorship*

Cameron, L. (Data Collection). Algorithmically Tethered Human Supply Chains

TEACHING CASES

Cameron, L. & Nguyen, B. " (2021). Man Against the Machine: Wrestling with Automated Bots in Amazon Delivery Services"

Cameron, L. & Lawson, J. (2020). "Fighting to Stay Alive: Uber and its Drivers during the COVID-19 Pandemic and Prop-22 "

Cameron, L. & Lawson, J. (2020). "Calling in vs. Calling Out: Handling Micro-Aggressions in Virtual Communications Channels"

Cameron, L. & Lawson, J. (2020). "Fostering Inclusiveness in Remote Work Environments"

TEACHING

University of Pennsylvania, Wharton School
Instructor

- MGMT 6120: Managing the Emerging Enterprise. MBA Core. Spring 2020, Spring 2021, Spring 2022, Fall 2022, Spring 2023, Fall 2023, Fall 2024, Spring 2025, Fall 2025
- MGMT 6130: Managing the Established Enterprise. Global WEMBA Core. Summer 2025
- MGMT 9740: Contemporary Issues in Work, Employment, and Organizations. Doctoral Course. Spring 2023, Spring 2026
- MGMT 9610: Making a Contribution: Theorizing from Novel Contexts. Doctoral Course. Spring 2022
- MGMT 9700: Applied Research Methods: Introduction to Qualitative Methods. Doctoral course. Spring 2022, Fall 2023, Fall 2025

- MGMT 9703: Qualitative Research Practicum: Data Collection & Analysis. Doctoral Course. Spring 2025.
- MGMT 9320a: Qualitative Research Practicum: Data Collection. Doctoral course. Spring 2020, Spring 2021, Spring 2023
- MGMT 9320b: Qualitative Research Practicum: Data Analysis. Doctoral Course. Fall 2020.
- MGMT 699: Independent Study on The Future of Work & AI. Graduate Course. Summer 2023
- MGMT 199: Independent Study on Smart Cities & Transportation. Undergraduate Course. Spring 2020
- Various masterclasses for prospective students on the future of work
- Multiple modules in executive education on the future of work, algorithmic management, power and influence, negotiations, diversity, and human and social capital

Teaching Assistant

- MGMT 898: Leadership, Conflict, and Change: Lessons from Rwanda. MBA elective course. Spring 2018.
    - Assisted class on immersion trip to Rwanda

University of Michigan, Ross School of Business
Instructor

- MO 300: Organizational Behavioral Theory in Management. BBA Core Course. Fall 2015.
    - Co-designed new core class leading curriculum development on income inequality, diversity, social intrapreneurship, and worker engagement

Teaching Assistant

- MO 705: Group Independent Study on the On-Demand Economy. MBA elective course.
- MO 302: Positively Leading People and Organizations. BBA elective course.
- EMBA 634. Negotiations. EMBA elective course.
- MO 615. Managing Professional Relationships. MBA elective course
- MO 604. Leadership Development. Weekend MBA core class.
- STRAT 441. Business and Society. BBA elective course
    - Assisted class on an immersion trip to Ghana
- Inter-group Relations Dialogue (IGR)
    - Led group dialogues on stereotyping, prejudice, and allyship

Guest Faculty, Summer Schools, and Lectures

- Crafting Your Research Identity, IESE Business School, Barcelona, Spain, Fall 2024. Topic: *Research Identity*
- Introduction to Qualitative Research Methods; Indian School of Business, Hyderabad, India; Workshop, Summer 2024. Topic: *Qualitative Research Methods*
- Fellowship at Auschwitz for the Study of Professional Ethics (FASPE), Berlin, DE & Krakow, PL; Faculty; Graduate Summer School, Summer 2024. Topic: *AI, Technology & Ethics*
- Computer Science Department, Princeton University, Princeton University, NJ. Undergraduate Guest Lecture; Spring 2024. Topic: *Future of Work and Algorithmic Management*
- Ross School of Business, University of Michigan, Ann Arbor, MI. Doctoral Guest Class; Fall 2023. Topic*: Theoretical Mechanisms*
- Medici Summer Institute, hosted by MIT, HEC & Bologna, Cambridge, MA. Faculty, Doctoral Summer School; Summer 2023. Topic: *Sociology of Work, Algorithmic Management & Gig Work*
- Summer Institute in Computational Social Science, hosted by Howard University, Washington, DC. Doctoral Summer School; Summer 2023. Topic: *Future of Work*
- Darden School of Business, University of Virginia, Charlottesville, VA. MBA Guest Lecture; Spring 2023. Topic*: Algorithmic Management*
- Wharton Global Youth Summer Speaker Series, Philadelphia, PA. High School Guest Lecture (150+ participants); Summer 2022. Topic: *Human and Social Capital*
- Introduction to Qualitative Research Methods; University of Michigan, Ann Arbor, MI; Workshop, Spring 2021. Spring 2022. Topic: *Qualitative Research Methods*

- Department of Materials Science and Engineering, University of North Texas. Doctoral Guest Lecture; Fall 2000. Topic: *Nuclear Magnetic Resonance*

DOCTORAL STUDENT TRAINING AND ADVISING

University of Pennsylvania

- **Dissertation Committee**
  - Elif Birced, Sociology, Boston University
  - Sharicca Boldon, Education
  - Jeremy Lewis, Organization Studies, University of North Carolina-Charlotte
  - Percyval Bayane, Sociology, University of Johannesburg, South Africa
  - Enrique Labarthe, Education [Placement: *Graduate Director and Dean of Business Faculty, Universidad de Ingenieria y Tecnologia*]
- **Comprehensive Exams**
  - Zorina Chen, Wharton (management)
  - Joyce Kim, Sociology
- **Post-Doctoral Fellow**
  - Elena Wong (co-advisor w/K. Klein)
- **Pre-Doctoral Fellow**
  - Michelle Borges (co-advisor w/L. Pongeluppe)
- **Undergraduate thesis**
  - Anthony Wright
  - Brandon Nguyen [Placement: *Completed master's program at London School of Economics*]
- **General Advising**
  - Kalie Mayberry [Placement: *Industry, program manager at Harvard University's Berkman Klein Center for Internet and Society*]

University of Michigan

- **Undergraduate thesis**
  - Sean Dew
  - Chloe Sosenko
- **General Advising**
  - Jordan Nye Fekete [*In PhD program in management at University of Michigan*]
  - Erica Johnson [*Completed PhD program in management at Case Western University*]
  - Katherine Johnson [*Completed master's program in positive psychology at University of Pennsylvania*]
  - Ines Hadziegric [*Completed research-based master's at Columbia University*]

AWARDS, HONORS, AND FELLOWSHIPS

2025 Penn Postdoctoral Association Mentorship Award
Winner, Responsible Research in Business and Management, Academy of Management Fellows and the Community for Responsible Research in Business and Management
Best Published Paper Award, (CTO Division, Academy of Management)
Honorable Mention, Distinguished Scholarly Article Award (LLM Section, American Sociological Association)
John T. Dunlop Outstanding Scholar Award, Labor and Employment Relationships Association
Best Paper Award (Labor and Employment Relationships Association, one of best overall submissions)
Responsible Research in Business Education Award, *Financial Times*
Women on the Move, *ONYX Magazine*

2024 Best Paper Award (Labor and Employment Relationships Association, one of best overall submissions)
Showcase Symposium (OMT/MOC/OB Division, Academy of Management)

2023 Wharton Teaching Excellence Award
40 Under 40 MBA Professors, Poets and Quants
Fellow (Member), School of Social Sciences, Institute for Advanced Study, Princeton (2023-2024)
Best Published Paper Award, (CTO Division, Academy of Management)
Outstanding Reviewer Award, Academy of Management Discoveries
Showcase Symposium (OMT/MOC/OB Division, Academy of Management)
Best Symposium Award (MOC Division, Academy of Management)
OMT Junior Faculty Consortium

2022 Faculty Fellow, Data & Society Research Institute
Fellow, Aspen Ideas Festival
Best Paper Award (HR Division, Academy of Management, best overall submission)
Showcase Symposium (OMT/MOC/OB Division, Academy of Management)

2021 Winner, Industry Studies Association's Dissertation Award
Finalist, Grigor McClelland Doctoral Dissertation Award, European Group of Organizational Studies
Runner-up, Louis Pondy Dissertation Award, Academy of Management
Best Symposium Award (MOC Division, Academy of Management)
Academy of Management Best Paper Awards (OMT & CTO/OCIS Division, top 10% of submissions)

2020 Winner, Psychology of Technology Dissertation Award
Winner, Likert Dissertation Paper Prize, University of Michigan
Winner, Giarratani Rising Star Award, Industry Studies Association (with Hatim Rahman)
Academy of Management Best Paper Award (MOC Division, top 10% of submissions)
LERA Competitive Papers, Labor and Employment Relations Annual Meeting

2019 OMT Above and Beyond the Call of Duty Reviewer Award (top 2% of reviewers)
Fellow, CASBS (Center for Advanced Studies of the Behavioral Sciences), Summer Institute for Organizations and their Effectiveness, Stanford University

2018 Ross School of Business, Ruth and Gilbert Whitaker Doctoral Fellowship
OB Doctoral Student Consortium, Academy of Management

2017 Pre-Doctoral Fellow (funded visiting student), Wharton School, University of Pennsylvania
Bouchet Honor Society
Ross Research Grant, University of Michigan

2016 Ruth and Gilbert Whitaker Doctoral Fellowship
Fellow, Medici Summer Institute, MIT-HEC Paris-Bologna Business School
GDO Doctoral Student Consortium, Academy of Management
GEBA Scholarship

2015 Audience Choice Award, Rackham Three-Minute Thesis Competition

2014 Fellowship, Arts and Citizenship (now Mellon Public Humanities), University of Michigan
Showcase Symposium (MSR Division, Academy of Management)
Rackham Conference Travel Grant, 2014 - 2018

2013 Rackham Merit Fellowship, University of Michigan, 2013 - 2019
Rackham Doctoral Fellowship, University of Michigan, 2013- 2019
Ross Regent Fellow, University of Michigan, 2013 - 2014

2000 – 2005 (Selected)
Honorable Mention, Siemens-Westinghouse Science Competition (formerly Intel Science

Competition)
Young American of the Year, Boy Scouts of America
Rotary Ambassadorial Scholar to Cairo, Egypt
First Team, USA Today All-Academic Team
Bill Gates Millennium Scholar
John Harvard Scholarship
Stokes Scholar at the National Security Agency
Coca-Cola National Scholar
National Achievement Scholar
Research Grants, Harvard University (electrical engineering)
Research Grants, University of North Texas (materials science and engineering)

INVITED PRESENTATIONS

2026

- Department of Industrial and Labor Relations, Cornell University, Ithaca, NY
- Organisational Theory and Information Systems Group, Judge School of Business, Cambridge University, Cambridge, UK
- Strategy and Entrepreneurship Department, University College London, London, UK
- Management and Entrepreneurship Department, Imperial College, London, UK
- Said School of Business, Oxford University, Oxford, UK
- Anthropology Department, Oxford University, Oxford, UK
- LeBow College of Business, Drexel University, Philadelphia, PA
- Centre for the Futures of Work, Information & Technology, Syracuse University, Syracuse, New York
- Washington Employment Group, Washington, DC
- Social Contagions, Artificial Intelligence, and Democracy Workshop, University of Virgina, Charlottesville, Virgina
- Culture Connect Conference, Haas School of Business, University of California at Berkeley, Berkeley, CA, *Keynote,* AI, Algorithmic Management and Culture

2025

- Columbia-Cornell Political Economy of Work, Junior Scholars Consortium, New York, New York
- Norwich Business School, University of East Anglia, Norwich, UK
- Carey School of Law, University of Pennsylvania, Corporate Roundtable on AI and Governance, *Panelist*
- Computer Science Department, Wellesley College, Wellesley, MA
- Kellogg School of Management, Northwestern University, Evanston, IL
- Transition Research Group, George Mason University, Fairfax, VA
- Wharton-INSEAD Doctoral Consortium Panel, Fontainebleau, France
- Adderley Positive Research Incubator Ross School of Business, Univ. of Michigan, Ann Arbor, MI; Discussant (Seed Generator)
- AlgoWork Roundtable, Department of Law and Economics, Technical University of Darmstadt, Darmstadt, Germany
- Organizational Behavior Department, Washington University in St. Louis, St. Louis, MO
- Sociology Department, University of Pennsylvania, Philadelphia, PA
- Symplatform, Lecco, Italy (declined due to scheduling conflict)
- Work2025, Turku, Finland
- American Sociological Association, Chicago, IL; *President's Panel* (declined due to scheduling conflict)
- Academy of Management Meeting, Copenhagen, Denmark
- European Group of Organizational Studies, Athens, Greece, *Presenter and Sub-group convener for Technology and Global Work*
- Labor and Employment Relationships Association, Seattle, WA (*Best paper presentation)*
- May Meaning Meeting, Washington, MI

- Positive Organizational Scholarship Research Conference, Ann Arbor, MI
- Financial Well-Being Seminar, Wharton School, University of Pennsylvania
- Global Institute for Artificial Intelligence and Business Analytics, Temple University, Philadelphia, PA
- Qualitative Research Methods Conference, Albuquerque, NM
- Summit @ Wharton (PhD Recruitment event), *Panelist*
- Digital Labor Futures Group, *Critic in Author Meets Critic Session*
- Women in Data Science, AI at Wharton Initiative, University of Pennsylvania, *Keynote* (rescheduled due to university closure)
- Reimagining the Future of Work, American Sociological Association, Virtual
- Culture Connect Conference, Haas School of Business, University of California at Berkeley, Berkeley, CA, *Keynote,* AI, Algorithmic Management and Culture, *Keynote* (declined due to scheduling conflict)

2024

- Renaissance Weekend, Charleston, SC; *Panelist, Presenter,* Algorithmic Management & Future of Work
- Wharton Executive Education End of the Year Alumni Dinner; *Keynote,* Mindfulness and Conflict Management
- Labor and Technology End of the Year Awards Ceremony, virtual; *Panelist,* Researching in Labor Tech
- IESE Business School, Barcelona, Spain
- ESADE Business School, Barcelona, Spain
- Università della Svizzera Italiana, Lugano, Switzerland
- Innovation Department, Swiss Federal Institute of Technology (ETH), Zurich, Switzerland
- Recovering the Lost Mandate: Integrating the Study of Work, Occupations, and Institutions, Special Alberta School of Business Strategy, Entrepreneurship & Management Workshop, University of Alberta, Edmonton, Alberta, Canada. *Keynote*
- Institute for Work and Employment Research, Sloan School of Business, MIT, Cambridge, MA
- Rapid Research, Wharton School, University of Pennsylvania
- Protections for Human-Subjects Researchers Under Threat of Subpoena, Princeton, NJ, *Panelist*
- Academy of Management Meeting, Chicago, IL, *Showcase Symposium*
- Labor and Employment Relationships Association, New York, NY (*Best paper presentation)*
- Wharton International Symposium, New Delhi, India
- Indian School of Business, Hyderabad, India
- International Communications Association, Philadelphia, PA (declined due to scheduling conflict)
- May Meaning Meeting, Philadelphia, PA
- Future of Work Summit, Northeastern University and Boston College, Boston, MA; *Discussant*
- Northeastern Qualitative Methods Conference, virtual; *Panelist, 500+ participants*
- AI and the Future of Work, Aspen Institute, *Panelist*
- People Analytics Conference, Wharton School, Univ. of Pennsylvania, Philadelphia, PA, *Presenter, 75+ participants*
- Wharton School, Univ. of Pennsylvania, Philadelphia, PA; *Fireside Chat,* Algorithmic Management
- Computer Science Department, Princeton University, Princeton, NJ
- Center for Business Ethics, Bentley University, Waltham, MA
- Institute for Advanced Study, Princeton, NJ
- Feminist Perspectives on Digital Capitalism, Harvard Radcliffe Institute, Cambridge, MA; *Panelist*
- Adderley Positive Research Incubator Ross School of Business, Univ. of Michigan, Ann Arbor, MI; Discussant (Seed Generator)

2023

- Renaissance Weekend, Charleston, SC; *Panelist, Presenter,* Algorithmic Management & Future of Work
- Sociology Department, Princeton University, Princeton, NJ; *Panelist,* Future of Work
- Society for the Social Studies of Science (4S), Honolulu, Hawaii
- People and Organizations Conference, Philadelphia, PA; *Plenary presentation*
- Responsible Research and Innovation Research Initiative, San Francisco State University, San

Francisco, CA; *Keynote,* Future of Work
- Machine Learning Studies in Management, Academy of Management Journal (AMJ) Paper Development Workshop, Cambridge, MA; *Panelist & Workshop Facilitator*, Future of Work
- Wharton School, Univ. of Pennsylvania, Philadelphia, PA; *Fireside Chat,* Algorithmic Management
- Strategic Management Society Conference, Toronto, Canada; *Panelist,* Strategic Human Capital Track
- Management and Organizations Seminar, Ross School of Business, Univ. of Michigan, Ann Arbor, MI
- WORK 2023, Turku, Finland
- American Sociological Association, Philadelphia, PA; *Paper Presentation, President's Panel;* Future of Work
- Platform Economies, American Sociological Association, Philadelphia, PA
- Academy of Management Meeting, Boston, MA *Discussant; Panel Moderator* (Best Symposium Award – MOC Division, Symposium)
- Junior OT Scholars Conference, London, UK
- European Group of Organizational Studies, Sardinia, Italy, *Sub-group convener, Technology & Equity & Paper Presentation*
- Society for the Advancement of Socioeconomics, Rio de Janeiro, Brazil
- Labor Futures, Labor Research and Action Network, Washington, DC; *Panelist,* Customer Activism in Gig Work
- PPM School of Management, Jakarta, Indonesia, *Keynote*, Future of Work
- 9th Global Conference on Business Mgmt. & Social Science, Dubai, UAE, *Keynote,* Future of Work
- Methodology, Organization, and Management (MOM): Technological Adoption and Human-Algorithm Interaction, Harvard Business School, Cambridge, MA
- May Meaning Meeting, Litchfield, CT
- Department of Technology Management, University of California at Santa Barbara, Santa Barbara, CA
- Future of Activism Research Workshop, Kellogg School of Management, Northwestern University
- Guanghua School of Management, Peking University, Beijing, China
- Darden School of Business, University of Virginia, *Fireside Chat,* Algorithmic Management
- Qualitative Research Methods Conference, Albuquerque, NM
- Blackbox Lab, Harvard Business School, Cambridge, MA
- Precarity Lab, Questrom School of Business & Sociology Department, Boston University, Boston, MA
- Strategy Department, Questrom School of Business, Boston University, Boston, MA
- D'Amore-McKim School of Business, Northeastern University, Boston, MA
- Management & Strategy Group, University of Hong Kong, Hong Kong

2022
- Strategy and Innovation Group, London Business School, London, UK
- Youth Economics Initiative, EconBowl, *Masterclass, 400+ participants*
- Ethnographic Café, Organizational Ethnography Special Workshop, *Panelist, 100+ participants*
- Consortium of Advanced Research Methods, Ph.D. Series, *Panelist, 30+ participants*
- Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA
- AI in Society Summit (hosted by University of Chicago), Chicago, IL,*Panelist*
- People and Organizations Conference, Philadelphia, PA
- Fox School of Business, Temple University, Philadelphia, PA
- Katz Graduate School of Business, University of Pittsburgh, Pittsburgh, PA
- Junior OT Scholars Conference, Ann Arbor, MI
- Academy of Management Meeting, Seattle, WA (*Best Paper Award – Human Resource Division; Showcase Symposium Management and Organizational Cognition Division)*
- Industry Study Association Conference, Philadelphia, PA
- Ph.D. Prep Series, Consortium of Advanced Research Methods (CARMA), Panelist
- 10th Biennial Positive Organizational Scholarship Research Conference, Ann Arbor, MI
- *The Great Return to Work: Ensuring Individual and Organizational Well-Being in the New Normal,* Boundless Leadership, Nalanda Institute for Contemplative Leadership, *Panelist, 175+ participants*
- Wharton Global Youth Summer Speaker Series, 2022, *Masterclass, 150+ participants*
- May Meaning Meeting, virtual
- Rapid Research, Wharton School, University of Pennsylvania, Philadelphia, PA

- Leavey School of Business, Santa Clara University, Santa Clara, CA
- UC-Davis Qualitative Conference, Davis, CA
- Worker Misclassification Taskforce, Commonwealth of Pennsylvania, Department of Labor

2021

- Renaissance Weekend, Charleston, SC, *Panelist + Moderator, *Cancelled due to COVID-19*
- Book Club on African American culture, *Presentation,* African-American genealogy
- Black Summit Solstice, virtual, Mindfulness and conflict management, *Presentation + Interactive exercise*, *150+ participants*
- Sociology Department, University of Pennsylvania, Philadelphia, PA
- Algorithmic Workplace Research Group, Sociology Department, Boston College, Boston, MA
- Weatherhead School of Management, Case Western University, Cleveland, OH
- Pennsylvania State Senate Democratic Policy Committee, Philadelphia, PA
- Decision Process Seminar, Wharton School, University of Pennsylvania, Philadelphia, PA
- Labor & Technology Discussion Series, virtual
- AI in the Global South, Data & Society, virtual, *active listener*
- Governor's Office of General Counsel, Commonwealth of Pennsylvania, *Presentation + Interactive exercise on mindfulness & conflict management, 500+ participants*
- People and Organizations Conference, Philadelphia, PA
- Future of Leadership Summit: Future of Recruiting, virtual, *Ted-style Talk w/ Q&A, 50+ participants*
- Changing Nature of Work, Stanford University, Stanford, CA
- Academy of Management Meeting, virtual (*Showcase Symposium & Best Symposium – Management and Organizational Cognition Division)*
- Society for the Advancement of Socio-Economics, virtual, *Panelist & Paper Presentation*
- Early Scholar Career Development Workshop, Society for the Advancement of Socio-Economics, virtual (declined due to scheduling conflict)
- American Sociological Association, Work and Occupations Division, virtual
- European Group of Organizational Studies, virtual, *Award Paper Presentation*
- Industry Study Association Conference, virtual, *Award Paper Presentation*
- Data & Society, The Hustle Economy: Race, Gender, and Entrepreneurship, virtual, *Collaborator*
- Labor and Employment Relations Association Conference, virtual
- International Labor Process Theory Conference, Greenwich, UK
- Predoctoral Fellowships Excellence Through Diversity Seminar, Philadelphia, PA, *Keynote*
- McCombs School of Business, University of Texas at Austin, Austin, TX
- Tepper School of Business, Carnegie Mellon University, Pittsburgh, PA *(PhD Proseminar)*
- Computer-Human Interactions Conference, This Seems to Work: Designing Technological Systems with The Algorithmic Imaginations of Those Who Labor, virtual, *Organizer & Panelist* for all-day workshop
- Society for Industrial-Organization Psychology, New Orleans, LA, *Panelist*
- Strategy & Organisational Behaviour Group, Imperial College, London, UK
- Future of Work Seminar, New York University, New York, New York
- Flash Talk, Wharton School, University of Pennsylvania, Philadelphia, PA
- University of Michigan, Interdisciplinary Committee on Organizational Studies (ICOS), Ann Arbor, MI *(Award Paper Presentation)*

2020

- People and Organizations Conference, Philadelphia, PA, *Plenary presentation*
- Digital Partners Seminar, Organizational Behavior Group, Stanford University
- Marketplace, Algorithms & Design Seminar, Columbia University & Stanford University, *Discussant*
- Rotary Club, Southwest Dallas County, TX, *Keynote*
- American Sociological Association, Work and Occupations Division, San Francisco, CA*, Panel Discussant*
- Academy of Management, Vancouver, BC, Canada
- PhD Project, Management Doctoral Student Conference, Vancouver, BC, Canada
- Microsoft, New Futures of Work Symposium, Redmond, WA

- European Group of Organizational Studies, Hamburg, Germany
- Flash Talk, Wharton School, University of Pennsylvania, Philadelphia, PA
- Industry Study Association Conference, Boston, MA, *Discussant & Award Paper Presentation, Critic in Author Meets Critic Session*
- May Meaning Meeting, Boston, MA
- Aspen Institute, Translating Research to Practice, Ann Arbor, MI, *Panel Keynote & Paper Presentation*

2019

- Future of Work Summit, Microsoft, Redmond, Washington, *TED-style Presentation,* 200+ participants
- Algorithms on the Shop Floor, Data & Society, New York, New York
- 9th Biennial Positive Organizational Scholarship Research Conference, Ann Arbor, MI
- Sharing Economy Conference, Northeastern University, Boston, MA, *Panelist and Paper Presentation*
- Working in America, Aspen Institute, Washington, DC, *Panelist*

2018

- Graduate School of Business, Stanford University, Stanford, CA
- Strategy Department, Ross School of Business, University of Michigan, Ann Arbor, MI
- Ledner College of Business, University of Delaware, Newark, DE
- Wharton School, University of Pennsylvania, Philadelphia, PA
- Johnson School of Business, Cornell University, Ithaca, NY
- Organizational Behavior Unit, Harvard Business School, Cambridge, MA
- Marshall School of Business, University of Southern California, Los Angeles, CA
- School of Engineering, Stanford University, Stanford, CA
- Sauder School of Business, University of British Columbia, Vancouver, British Columbia, Canada
- Lundquist School of Business, University of Oregon, Eugene, OR
- Industrial and Labor Relations School, Cornell University, Ithaca, NY
- Owens School of Business, Vanderbilt University, Nashville, TN
- Ivey School of Business, University of Western Ontario, London, Ontario, Canada
- Aspen Institute, Working Towards Shared Prosperity, Ann Arbor, MI *Panelist*
- People and Organizations Conference, Philadelphia, PA
- Ford Foundation, Constructing Rights for a 21st Century Workforce, New York, NY, *Panelist*
- Haslam School of Business, University of Tennessee, Knoxville, TN
- Academy of Management, Chicago, IL
- Harvard Law School, Clean Slate Initiative, Cambridge, MA, *Panelist*
- University of Pennsylvania, Wharton Center for Human Resources, Philadelphia, PA, *Keynote*
- Data and Society, New York, New York, *Invited Roundtable Participant*
- Conference on Social Innovation, Ann Arbor, MI
- May Meaning Meeting, Houston, TX
- University of Michigan, Center for Positive Organizations Research Incubator, Ann Arbor, MI
- Social Impact Initiative, Wharton School, University of Pennsylvania, Philadelphia, PA

2017

- Flash Talk, Wharton School, University of Pennsylvania, Philadelphia, PA
- American Sociological Association, Montreal, Quebec, Canada
- Academy of Management, Atlanta, GA
- Critical Management Studies Conference, Liverpool, UK
- 8th Biennial Positive Organizational Scholarship Research Conference, Ann Arbor, MI
- May Meeting Meaning, Boston, MA
- Harvard Gender and Leadership Conference, Cambridge, MA
- Likert Dissertation Fair, University of Michigan, Ann Arbor, MI

2016

- Interdisciplinary Consortium on Organizational Studies, University of Michigan, Ann Arbor, MI
- Academy of Management, Anaheim, CA

- International Process Symposium, Corfu, Greece
- University of Michigan, Center for Positive Organizations Research Incubator, Ann Arbor, MI
- May Meaning Meeting, San Francisco, CA

2015

- Academy of Management, Vancouver, BC, Canada
- International Positive Psychology World Congress. Orlando, FL.
- 7th Biennial Positive Organizational Scholarship Research Conference, Orlando, FL
- 3MT Thesis Competition, Ann Arbor, MI (*Audience Choice Award)*
- May Meaning Meeting, New Haven, CT
- Society for Industrial-Organization Psychology, Philadelphia, PA

2014

- Academy of Management, Philadelphia, PA (*Showcase Symposium – Management & Spirituality Division)*
- Hamtramck Historical Museum, Hamtramck, MI
- May Meaning Meeting, Minneapolis, MN
- University of Michigan Positive Research Incubator, Ann Arbor, MI

2013

- International Association of Cross-Cultural Psychology, Los Angeles, CA

2005 - 2010

- American History through the Eyes of African American Genealogy, US State Department Middle East Partnership Initiative, Algiers and Ouargla, Algeria
- Symposium Malien sur Sciences Appliquées, Bamako, Mali
- American History through the Eyes of African American Genealogy, local genealogy association, Laurel, MD
- Undergraduate Research Symposium, Harvard College, Cambridge, MA

PROFESSIONAL SERVICE

A. Editorial Service

Editorial Board

- Organization Science, 2025+
- Administrative Science Quarterly, 2024+
- Socio-Economic Review, 2023-2027

Ad-Hoc Reviewing

- Academy of Management Annual Meeting, Academy of Management Discoveries, Academy of Management Journal, Academy of Management Perspectives, Academy of Management Review, American Sociological Review, Association of Computing Machinery, British Journal of Industrial Relations, Cambridge Journal of Regions, California Management Review, Critical Sociology, Economy and Society, Fairness, Accountability and Transparency Conference (FACCT), Human Resource Management, Industrial and Labor Relations Review, Industrial Relations, Journal of Computer Mediated Communications, INFORMS/ Organization Science Dissertation Proposal Competition, Journal of Organizational Behavior, Journal of Management, Journal of Management Studies, National Science Foundation , Management of Information Science Quarterly, Social Forces, Sociological Perspectives, Sociology of Race and Ethnicity, Sustainability, Organization Science, Organizational Theory, Transactions in Computer Human Interactions, Washington Center for Equitable Growth, Work and Occupations, Work, Employment and Society

B. Wharton Service

Management Department, Wharton School, University of Pennsylvania
- Founder and Co-Organizer (w/ J. Kirtley), Qualitative Methods Workshop, 2024+
- Member, Seminar Committee, 2024- 2025
- Co-Organizer (w/ A. Gatignon), OT Paper Workshop, 2022-2023
- Member, Doctoral Program Committee, 2020 – 2023; 2025 - 2026
- Co-Founder & Co-Organizer (w/M. Parke), Research 2.0: professional development seminar for students, 2020-2023

Wharton School, University of Pennsylvania
- Panelist, Summit @ Wharton (PhD Recruitment event), 2025
- Masterclass, Winter Welcome Weekend, 2025
- Coordinator, Workshop: Improv for Teaching and Presentations, 2023
- Wharton Global Youth Summer Speaker Series, 2022
- African & African American MBA Student Association Speaker Series, 2021
- Masterclass, Explore Wharton, MBA recruitment, 2020+
- Panelist, IDDEAS @ Wharton (PhD Recruitment event), 2020 **Cancelled due to COVID-19*

University of Pennsylvania
- Predoctoral Fellowships Excellence Through Diversity Seminar, 2021 *(Keynote)*

C. <u>University of Michigan Service</u>

Management & Organizations Department, Ross School of Business, University of Michigan
- Qualitative Methods Workshop for PhD students, 2021, 2022
- Connections Czar, 2018 – 2019
- Alumni Relationships Coordinator, 2015 - 2017
- Member of the Doctoral Admissions & Recruiting Committee, 2014
- AOM Reception Planning Committee, 2014
- First-Year Cohort Representative, 2013 – 2014

Rackham Graduate School, University of Michigan
- Reviewer, Bouchet Society, 2022
- Co-Organizer (w/C. Hoffman), Interdisciplinary Working Group on Qualitative Methods, 2016 - 2017

D. <u>Academic Community Service</u>

National Science Foundation (NSF)
- Panel and Individual Reviewer, Future of Work and Organizations, 2022+

Washington Center for Equitable Growth
- Panel Reviewer, Promoting Competition and Supporting Workers in an Era of AI Innovation, 2025

Center for Positive Organizations, University of Michigan
- Conference Organizer, Positive Organizations Scholarship Conference, 2025
- Seed Generator, Research Incubator Series, 2024
- Faculty Affiliate, 2019+
- Program Coordinator, Biennial Conference of Positive Organizational Scholarships, 2016 – 2017
- Doctoral Student Fellow, 2016 - 2017
- Doctoral Student Affiliate, 2014 – 2019

Ph.D. Project
- Committee Member, Programming, 2016 – 2017

- Committee Member, Research 2.0, 2013 – 2014

E. Conference Activities

Academy of Management Annual Meeting
- Associate Editor, CTO Division, 2025
- Faculty Mentor, OMT Doctoral Consortium, 2025
- Representative at Large, CTO Division, 2024 - 2027
- Chair, Best Conference Paper, Research Award Committee, HR Division, 2023
- Member, Research Awards Committee, OB Division, Research Awards Committee (Best Paper & Best Practitioner Paper), 2023+
- Member, Making Connections Committee, OB Division, 2022-2023
- Roundtable Facilitator, Doctoral Consortium, OMT Division, 2022
- Member, Research Awards Committee, OMT Division, 2020-2024
- Roundtable Facilitator, MOC Connect, MOC Division, 2021, 2022
- Roundtable Facilitator, Navigating Qualitative Dissertations, Research Methods Division, 2020-2022

Labor and Employment Relationship Association Conference (LERA)
- Program Committee, LERA@ASSA conference, 2025-6

European Group on Organizational Studies (EGOS)
- Sub-group convenor (w/P. Hinds & E. Matterelli), Emerging Technologies and Global Issues. 2025
- Sub-group convenor (w/P. Hinds & E. Matterelli), Emerging Technologies, Equity, and Inclusion: Problems and Solutions. European Group of Organization Studies, 2023

Junior Faculty Organizational Theory Conference (JFOT)
- Co-Organizer (w/ T. Yang), 2025

Industry Studies Association (ISA)
- Early Career Development Award Committee, Industry Studies Association, 2021 – 2024

People Analytics Conference
- Award Committee, White Paper Competition, 2025
- Keynote, 2024

Association of Computing Machinery (ACM - Annual Conference of Human-Computer Interaction Field)
- Program Committee, Accountability, and Transparency Conference, 2020-2022

Other Conferences
- Founder & Steering Committee, Gig Economy Micro-community, 2017 - 2019
- Steering Community, Mindfulness Micro-community, 2013 – 2016

E. Industry, Government, and Nonprofit Engagement

Industry Engagement
- Expert Witness Report for the Minnesota Attorney General re: Attorney General of Minnesota vs. Shipt, Inc., Fourth Judicial District. No. 27-CV-22-15991. 2024-2025
- Expert Witness. Attorney General of Massachusetts v. Uber Technologies, Inc. and Lyft, Suffolk Superior Ct. Docket No. 2084CV01519-BLS1. 2022-2024
- Expert Witness. Confidential Civil Litigations. 2021+
- Expert Testimony. Worker Misclassification and the Future of Work in PA, Pennsylvania House and Senate Democratic Policy, 2021

- Expert Testimony. Transportation Hearings, Pennsylvania State Senate policy sub-committee, 2019
- Advising. Confidential Civil, Criminal, and State Investigations. 2021+

U.S. Department of Labor

- Member, Work Arrangements Content Panel, National Youth Longitudinal Survey (2026), 2022-2023

Data and Society Research Institute

- Committee Member, Research and Policy, 2025
- Co-Organizer, Fellows Reunion, Data & Society Research Institute, 2023
- Organizer, Race & Technology Micro-Convening, Data & Society Research Institute, 2023

Advisory Boards

- Research Fellow, Centre for AI, Management, and Organizations, University of Hong Kong, 2025+
- Council Member, Partnership on AI, 2025+
- External Advisory Board, Center for the Future of Management, New York University, 2024+
- Research Advisory Board, Harvard Business Publishing Education, 2022-2023
- Research Advisory Board, Plymetrics, 2020

F. <u>Professional Associations</u>

- Academy of Management, 2011+
- American Sociological Association, 2017+
- Association of Black Sociologists, 2023+
- Eastern Sociological Society, 2014 - 2016, 2021-2022
- European Group of Organizational Studies, 2015+
- Industry Studies Association, 2020+
- International Positive Psychology Association, 2015
- Labor and Employment Relations Association, 2020+
- Management Faculty of Color, 2020+
- PhD Project, Management Doctoral Students Association, 2011 – 2020
- Society of Industrial-Organizational Psychology, 2015
- Society for the Study of Social Problems, 2020 - 2021

SELECT MEDIA MENTIONS

Wall Street Journal ♦ Financial Times ♦ Associated Press ♦ Newsweek ♦ NPR's Marketplace ♦ Forbes ♦ Washington Post ♦PBS NPR WHYY ♦Forbes ♦ Fast Company ♦ Harvard Business Review ♦ Milwaukee Independent ♦ Philadelphia Inquirer ♦ Boston Globe ♦ San Francisco Chronicle ♦ Seattle Post ♦ CT Insider ♦ Albany Times ♦ European Financial Times ♦ Liasons Sociales ♦ Human Resource Magazine ♦ Business Insider ♦ Bloomberg ♦ Inc. ♦World Economic Forum ♦ CNBC ♦The Skim ♦ Scripps News ♦ Kiplinger's ♦ Nikkei ♦ Morning Brew ♦ Vice ♦ Yoga Journal ♦ Daily Pennsylvanian

SELECT MEDIA FEATURES

Meet Your New Boss: An Algorithm. The Culture Toolkit with Jenny Chatman and Sameer Srivastava. 10 March 2025

About Algorithmic Management. Talking About Platforms with Philip Meier, Daniel Trabucchi, and Tommaso Buganza. 17 February 2025

How Algorithmic Management Manufactures Consent. Faculti. 17 December 2024.

Just Your Average Employee: How Gig Workers Experience Meaning at Work. IESE Business School. 11 December 2024.

Penn Professor Lindsey Cameron, Former Rideshare Driver, Reflects on Experience in FASPE Program. Daily Pennsylvanian. 5 November 2024.

Gender Empowerment and the Gig Economy: Insights from Dr. Lindsey Cameron. GirlsUp, United Nations Foundation. March 2024

The Need for Mindfulness, Reflection, and Inquiry in Our Busy World. Learning through Experience with Dr. Heidi Brooks. 3 July 2024.

IAS Term is Underway with 272 New, Returning Scholars. Town Topics. Fall 2023.

Meet a Hacker Turned Scholar: Q&A with Lindsey D. Cameron. Institute for Advanced Study. Fall 2023

2023 Best 40-Under-40 MBA professor, Lindsey Cameron, The Wharton School. Poets and Quants. Fall 2023.

Make a Way: Lindsey Cameron with Sareeta Amrute. Data and Society Research Institute. Summer 2023.

Does Mindfulness Actually Make You Happier (or Better) at Work? Ten Percent Happier with Dan Harris [National Top 10 podcast in mental health.] March 2023.

On the Gig Economy: An Interview with Lindsey Cameron. Accounts Newsletter, Official Newsletter of the Occupations & Work and Economic Sociology section of the American Sociological Association. Winter 2022.

Research Spotlight: Prof. Lindsey Cameron on Drivers in the Gig Economy. Wharton Social Impact Initiative. 29 November 2021

The Gig Economy and the Pandemic. Work and Life Podcast with Stew Friedman [National Top 15 in podcast in Work and Life]. February 2021.

- Used in graduate seminar

Research Spotlight: Lindsey D. Cameron, A Personal Impact in the Gig Economy's Impact. Center for Positive Organizations, University of Michigan. 19 October 2020.

Lindsey Cameron: USA Today All-Academic Team, First Team. USA Today. April 2001.

Young Women of Achievement: A Resource for Girls in Math, Science, and Technology. University of Mississippi Press. 2001.

RESEARCH GRANTS

Indian School of Business-Wharton Joint Research Initiative $17,000 (2024)

Wharton Dean's Research Fund, University of Pennsylvania*. Algorithmic Management*, $15,000 (2024)

Wharton Global Initiatives, Wharton School, University of Pennsylvania. *The Platform is Not Neutral: How Algorithmic Management Shifts Across Borders* $10,000 (2022), $8000 (2023), $7000 (2024)

AI for Business & Wharton Analytics, Wharton School, University of Pennsylvania. *The Trouble with Bots. Long Live the Bots!* $25,000 (2022)

Center for Human Resources, Wharton School, University of Pennsylvania. *The Limits of Uberification*, $9,000 (2021)

Center for Human Resources, Wharton School, University of Pennsylvania. *Gig Work and Organizing*, $9,000 (2021)

Center for Human Resources, Wharton School, University of Pennsylvania. *The Gig Worker and the Pandemic*, $14,000 (2020)

Wharton Dean's Research Fund, University of Pennsylvania*. Navigating Platform Conflict: A Multi-National Comparative Ethnography of the RideHailing Industry*, $16,200 (2020)

Mack Institute Research Fellowship, University of Pennsylvania. *Algorithmic Management in the On-Demand Economy,* $9500, (2019), $5200 (2020), $10,000 (2022), $10,000 (2023), $7500 (2004), $60,000 (2024-2026)

Undergraduate Research Opportunity Program, University of Michigan. *Precarious Work in the Gig Economy*, $500 - $1100 (2016, 2017, 2019)

Ross Doctoral Research Grant, University of Michigan. *Precarious Work in the Gig Economy*, $4000 (2017)

Rackham Doctoral Research Grant, University of Michigan. *Precarious Work in the Gig Economy*, $3000 (2017)

Rackham Doctoral Research Grant, University of Michigan *The ties that bind us: A process approach to understanding attachment within diverse communities*, $1500 (2015)

Undergraduate Research Opportunity Program, University of Michigan. *The ties that bind us: A process approach to understanding attachment within diverse communities*, $1100 (2014)

Center for Social Impact, Nonprofit Management Center, University of Michigan. *Ethnic Entrepreneurship and Identity,* $3750 (2014)

Harvard University undergraduate research grant for senior thesis, *A Human Powered Generator for West African Literacy Classes;* $7500 (2004)

Harvard University undergraduate research grant, *Designing Osmosis Systems for Desert Areas*, $1250 (2003)

Smithsonian Institute, *I.I. Rabi and Norman Ramsey: Using Electrons to Measure Magnetic Moments*, $4500 (2001)

University of North Texas undergraduate research grant; *Electromagnetic Properties and Beta Transitions of Polymer Hybrids.* $2750 (2000)

OTHER EDUCATION

Maryland University of Integrative Health (formerly Tai Sophia Institute)
Post-Baccalaureate Certificate, Transformative Leadership 2012

American University in Cairo
Intensive Arabic Study and Middle Eastern Political Science; Rotary Ambassadorial Scholar 2006

OTHER RESEARCH EXPERIENCE

University of Maryland, College Park, Maryland
Research assistant for Michele Gelfand on Arab culture and negotiations 2012- 2013

University of North Texas - Denton, Texas
Research assistant for Witold Brostow on polymer composition and stress fractures 2000 - 2001

INDUSTRY EXPERIENCE

National Security Agency & Central Intelligence Agency 2001 – 2013

- *Liaison Representative and Counter-terrorism Intelligence Analyst*
  - ● Only technical analyst in war zone providing computer network operations (CNO) support of counter-terrorism team. As first permanent, in-country representatives led cross-cultural, inter-agency teaming efforts resulting in dozens of successful operations. Briefed highest levels of US government including Commanding General of Multi-National Forces Iraq and US Ambassador. Wrote over 120 reports that were briefed to the highest levels including the White House and US Ambassador.
  - ● Operational usage of French and Arabic; completed over 300 hours of advanced language training. Designed and taught three multi-lingual analytical courses. Received six (6) exceptional performance awards and four (4) cash awards.
- *Team Lead and Network Analyst*
  - ● Researched and executed dozens of computer network operations (CNO); led team of eight. Extensive experience analyzing Windows, UNIX, routers, and firewalls machines.
  - ● Conducted technical all-source research on specific telecommunications system, wireless networks and technical lead on specific wireless technology. Learned and taught large-scale proprietary software tools for data management and data analysis.

CITIZENSHIP

US Citizen

EXHIBIT B - MATERIALS CONSIDERED

All citations and references in the Rebuttal Expert Report.

Uber Online Documentation:

Uber YouTube videos

Uber Documents:

UBER_JCCP_MDL_000007083

UBER_JCCP_MDL_000118138

UBER_JCCP_MDL_000167710

UBER_JCCP_MDL_000420013

UBER_JCCP_MDL_000960333

UBER_JCCP_MDL_000167081

UBER_JCCP_MDL_000397094

UBER_JCCP_MDL_000908315

UBER-MDL3084-000001295

UBER000144360

UBER_JCCP_MDL_000033001

#5363.1

#5471.1

UBER_JCCP_MDL_000119240

UBER_JCCP_MDL_000453907

UBER_JCCP_MDL_000960650

UBER_JCCP_MDL_002001300

UBER_JCCP_MDL_003259964

UBER-MDL3084-000065882

UBER_JCCP_MDL_000385408

UBER_JCCP_MDL_001721729

UBER_JCCP_MDL_000168086

UBER_JCCP_MDL_000213758

UBER_JCCP_MDL_000908746

UBER_JCCP_MDL_000031087

UBER_JCCP_MDL_000876347
UBER_JCCP_MDL_000875369
UBER_JCCP_MDL_002138070
UBER-MDL3084-000008700
#5321.1
UBER_JCCP_MDL_000108726
UBER_JCCP_MDL_000120466
UBER_JCCP_MDL_000124971
UBER_JCCP_MDL_000552868
UBER-MDL3084-000002832
UBER-MDL3084-000014618
UBER_JCCP_MDL_000172834
UBER_JCCP_MDL_000875766
UBER_JCCP_MDL_000185858
UBER_JCCP_MDL_0003259958
UBER_JCCP_MDL_0003259959
UBER_JCCP_MDL_0003259960
UBER_JCCP_MDL_0003259965
UBER-MDL3084-000065722
UBER_JCCP_MDL_000881555
UBER_JCCP_MDL_000584033
UBER_JCCP_MDL_000422799
UBER_JCCP_MDL_000605376
UBER_JCCP_MDL_000584015
UBER_JCCP_MDL_000549109
UBER000169934
UBER_JCCP_MDL_000202426
UBER000140928
UBER-MDL3084-000009784
UBER-MDL3084-000012512
UBER_JCCP_MDL_001545951

UBER_JCCP_MDL_001712067
UBER_JCCP_MDL_000323026
UBER_JCCP_MDL_000252298
UBER_JCCP_MDL_000167879
UBER_JCCP_MDL_000250635
UBER-MDL3084-000100806
UBER_JCCP_MDL_004237642
UBER000001250
UBER_JCCP_MDL_000007628
UBER-MDL3084-000085540
UBER000179489
UBER_JCCP_MDL_001406663
UBER_JCCP_MDL_003626900
UBER_JCCP_MDL_000349718
UBER_JCCP_MDL_000177759
UBER_JCCP_MDL_000877811
UBER-MDL3084-00000659
UBER-MDL3084-000000722
UBER-MDL3084-000008671
UBER-MDL3084-000012771
UBER-MDL3084-000061985
UBER000192116
UBER000211327
UBER_JCCP_MDL_001464695
UBER_JCCP_MDL_002308529
UBER-MDL3084-000066164
UBER_JCCP_MDL_000349702
#11700.1
#11479.1
#11688.1
UBER-MDL3084-000085035

UBER-MDL3084-000082007

UBER_JCCP_MDL_003300332

#11300.1

#11315.1

UBER-MDL3084-000003722

UBER-MDL3084-000000359

UBER-MDL3084-0000082007

UBER_JCCP_MDL002095522

UBER-MDL3084-000002770

UBER_JCCP_MDL_0003259965

UBER-MDL3084-000014742

UBER000206296

UBER-MDL3084-000081772

UBER-MDL3084-000047458

UBER-MDL3084-BW-00034324

UBER_JCCP_MDL_000532360

UBER000178305

UBER_JCCP_MDL_001115639

UBER-MDL3084-00000695

UBER_JCCP_MDL_001253453

UBER_JCCP_MDL_000084271

UBER_JCCP_MDL_004807096

UBER_JCCP_MDL_000537714

UBER_JCCP_MDL_003018349

UBER_JCCP_MDL_000508814

UBER_JCCP_MDL_003755190

UBER000184830

UBER-MDL3084-000055039

UBER_JCCP_MDL_000368807

UBER-MDL3084-BW-00000011

UBER-MDL3084-BW-00000015

UBER-MDL3084-BW-00000022

UBER-MDL3084-BW-00000029

UBER-MDL3084-BW-00000032

UBER-MDL3084-000000681

UBER_JCCP_MDL_000016203

UBER-MDL3084-000000621

UBER_JCCP_MDL_001535251

UBER_JCCP_MDL_000444051

UBER_JCCP_MDL_000366567

UBER_JCCP_MDL_003682988

UBER JCCP MDL 001105062

UBER JCCP MDL 003306684

UBER-MDL3084-000074502

UBER_JCCP_MDL_000323152

UBER_JCCP_MDL_003306684

UBER_JCCP_MDL_000516118

#11478.1

#11734.1

Other:

Expert report from Joseph Okpaku dated September 26, 2025 submitted in this matter

References:

Alkhatib, A., & Bernstein, M. (2019). Street-Level Algorithms: A Theory at the Gaps Between Policy and Decisions. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–13). Association for Computing Machinery.

Ashford, S. J., George, E., & Blatt, R. (2007). 2 old assumptions, new work: The opportunities and challenges of research on nonstandard employment. *Academy of management annals*, *1*(1), 65-117.

Anderson, M., McClain, C., Faverio, M., & Gelles-Watnick, R. (2021). Americans' Experiences Earning Money Through Online Gig Platforms. In The State of Gig Work in 2021. Pew Research Center. https://www.pewresearch.org/internet/2021/12/08/americans-experiences-earning-money-through-online-gig-platforms/

Ajunwa, I. (2023). *The Quantified Worker: Law and Technology in the Modern Workplace*. Cambridge University Press.

Bansal, P. & Corley, T. (2011). The Coming of Age for Qualitative Research: Embracing the Diversity of Qualitative Methods. *Academy of Management Journal, 54*(2), 233-37.

Bartunek, J.M., Rynes, S. L., & Ireland, R. D. (2006). What Makes Management Research Interesting, and Why Does It Matter? *The Academy of Management Journal, 49*(1), 9-15.

Batt, R. (1999). Work Organization, Technology, and Performance in Customer Service and Sales. *ILR Review*, *52*(4), 539-564.

Bechky, B. A. & O'Mahoney, S. (2015). *Leveraging Comparative Field Data for Theory Generation*. Routledge.

Bolino, M. C., & Grant, A. M. (2016). The bright side of being prosocial at work, and the dark side, too: A review and agenda for research on other-oriented motives, behavior, and impact in organizations. *Academy of Management Annals*, *10*(1), 599-670.

Borkholder, Joy, Mariah Montgomery, Miya Saika Chen, and Rebecca Smith. (2018). *Uber State Interference: How Transportation Network Companies Buy, Bully, and Bamboozle Their Way to Deregulation*. National Employment Law Association.

Burawoy, M. (1974). *Manufacturing Consent: Changes in the Labor Process under Monopoly Capitalism*. University of Chicago Press.

Burawoy, M. (1985). The Politics of Production: Factory Regimes Under Capitalism and Socialism. Verso Books.

Burawoy, M. (2017). On Desmond: The limits of spontaneous sociology. *Theory and Society*, *46*, 261-284.

Burrell, J. (2016). How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. *Big Data & Society*, *3*(1).

Cameron, L., (2018). *The Feminization of Gig Work.* Harvard Business School Gender and Race Conference. May 2018.

Cameron L. (2022). Making out While Driving: The Relational and Efficiency Game in the Gig Economy. *Organization Science.*

Cameron, L. (2024). The Making of the "Good Bad" Job: How Algorithmic Management Manufactures Consent through Constant and Confined Choice. *Administrative Science Quarterly.*

Cameron, L., Anteby, M., & Chan. (2022). Heroes from Above and But Not (always) from Within: Gig Workers Responses to the Sudden Moralization of their Work. *Organizational and Human Decision processes.*

Cameron, L., Lamers, L., Leicht-Deobald, U., Lutz, C., Meijerink, J., & Möhlmann, M. (2023). Algorithmic management: Its implications for information systems research. *Communications of the Association for Information Systems*, *52*(1), 23.

Cameron, L., & Meuris, J. (2022). The Perils of Paycheck Dispersion: When Fluctuation in Compensation Undermine Retention. n Sonia Taneja (Ed.), *Proceedings of the Eighty-second Annual Meeting of the Academy of Management.* Online ISSN: 2151-6561.

Cameron L, Rahman, H. (2022). Expanding the Locus of Resistance: Understanding the Co-Constitution of Control and Resistance in the Gig Economy. *Organization Science.*

Cameron, L., Rosenblat, A. (2020). Gig Work Used to Be a Recession-Proof Safety Net. Not Anymore. *Fast Company*. https://www.fastcompany.com/90537938/gig-work-used-to-be-a-recession-proof-safety-net-not-anymore

Cameron, L., Thomason, B., & Conzon, V. (2021). Risky Business: Gig Workers and the Navigation of Ideal Worker Expectations During the COVID-19 Pandemic. *Journal of Applied Psychology.*

Capoot, J. (2022). Uber unveils new features, including one that lets drivers choose the trips they want. CNBC News. Accessed on 3 Sept 2023 at https://www.cnbc.com/2022/07/29/uber-will-let-drivers-choose-the-trips-they-want-to-take.html.

Cardinal, L. B., Sitkin, S. B., & Long, C. P. (2004). Balancing and Rebalancing in the Creation and Evolution of Organizational Control. *Organization Science*, *15*(4), 411–431.

Chai, S., & Scully, M. A. (2019). It's about distributing rather than sharing: Using labor process theory to probe the "sharing" economy. *Journal of Business Ethics*, *159*, 943-960.

Charmaz, K. (1996). *Constructing Grounded Theory. A Practical Guide Through Qualitative Analysis.* Sage Publications.

Clemes, S. A., O'Connell, S. E., & Edwardson, C. L. (2014). Office Workers' Objectively Measured Sedentary Behavior and Physical Activity during and outside Working Hours. *Journal of Occupational and Environmental Medicine*, *56*(3), 298–303

Culpepper, P. D., & Thelen, K. (2020). Are We All Amazon Primed? Consumers and the Politics of Platform Power. *Comparative Political Studies*, *53*(2), 288–318.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative science quarterly*, *65*(3), 644-676.

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). *The business of platforms: Strategy in the age of digital competition, innovation, and power* (Vol. 320). New York: Harper Business.

Danaher, J. (2016). The Threat of Algocracy: Reality, Resistance and Accommodation. *Philosophy & Technology*, *29*.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining" gamification". In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments* (pp. 9-15).

Doctrow, C. (Jan 23 2023). The Enshitifcation of TikTok. *Wired.* Accessed on 30 July 2025 at https://www.wired.com/story/tiktok-platforms-cory-doctorow/

Dodge, M., & Kitchin, R. (2009). Software, objects, and home space. *Environment and Planning A*, *41*(6), 1344-1365.

Dubal, V. B. (2022). Economic security & the regulation of gig work in California: From AB5 to Proposition 22. *European Labour Law Journal*, *13*(1), 51-65.

Dubal, V. (2023). On algorithmic wage discrimination. *Columbia Law Review*, *123*(7), 1929-1992.

Edwards, P. (1986). *Conflict at Work: A Materialist Analysis of Workplace Relations*. B. Blackwell.

Fayol, H. (1949). *General and Industrial Management*. Pitman and Sons, Ltd.

Flamholtz, E. G., Das, T. K., & Tsui, A. S. (1985). Toward an integrative framework of organizational control. *Accounting, Organizations and Society*, *10*(1), 35–50.

Friedman, A. (1977). Responsible Autonomy Versus Direct Control Over the Labour Process. *Capital & Class*, *1*(1), 43–57.

Fuller, L., & Smith, V. (1991). Consumers' Reports: Management by Customers in a Changing Economy. *Work, Employment and Society*, *5*(1), 1–16.

Gandini, A. (2019). Labour process theory and the gig economy. *Human Relations*, *72*(6), 1039–1056.

Glaser, B., & Strauss, A. (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Mill Valley, CA: Sociology Press.

Grohmann, R., Pereira, G., Guerra, A., Abilio, L. C., Moreschi, B., & Jurno, A. (2022). Platform scams: Brazilian workers' experiences of dishonest and uncertain algorithmic management. New Media & Society, 24(7), 1611-1631.

Gillespie, T. (2018). Regulation of and by platforms. In J. Burgess, T. Poell, & A. Marwick (Eds.), *The SAGE Handbook of Social Media* (pp. 254–278). SAGE Reference.

Gitelman, L. (Ed.). (2013). *Raw data is an oxymoron.* MIT Press.

Goffman, E. (1963). Embarrassment and Social Organization. In N. J. Smelser & W. T. Smelser (Eds.), *Personality and social systems* (pp. 541–548). John Wiley & Sons, Inc..

Goldberg, A., Srivastava, S. B., Manian, V. G., Monroe, W., & Potts, C. (2016). Fitting In or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness. *American Sociological Review*, *81*(6), 1190–1222.

Hannák, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., & Wilson, C. (2017). Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing* (pp. 1914-1933).

Heiland, H. (2025). The social construction of algorithms: A reassessment of algorithmic management in food delivery gig work. *New Technology, Work and Employment*, *40*(1), 1-19.

Hern, A. (2016). Uber and Lyft pull out of Austin after locals vote against self-regulation. The Guardian.
https://www.theguardian.com/technology/2016/may/09/uber-lyft-austin-vote-against-self-regulation

Hill, J. D. (2020). *The Hustle Ethic and the Spirit of Platform Capitalism*. Stanford University.

Hochschild, A.R. (1983). *The managed heart: commercialization of human feeling*. University of California Press.

Hochschild, A. R. (2018). *Strangers in their own land: Anger and mourning on the American right*. The New Press.

Hu, W. (2022). *Inside the fight to pay delivery drivers 22 and Hour.* New York Times. Access at: https://www.nytimes.com/2022/12/08/nyregion/nyc-food-delivery-workers-wage-increase.html

Huet, E. (Jan 22 2015). Uber's Ever Renewing Workforce. *Forbes.* Accessed on 30 July 2025 at https://www.forbes.com/sites/ellenhuet/2015/01/22/uber-study-workforce/

Irani, L. (2013). The cultural work of microwork. New Media and Society. Volume 17, Issue 5.

Isaac, M. (2019). *Super pumped: The battle for Uber*. WW Norton & Company.

Isaac & Lohr (2017). Unroll.me Service Faces Backlash Over a Widespread Practice: Selling User Data. New York Times

Isaac, M. (2017). Uber Ceo's Plays with Fire. New York Times.

Joyce, K., Smith-Doerr, L., Alegria, S., Bell, S., Cruz, T., Hoffman, S. G., ... & Shestakofsky, B. (2021). Toward a sociology of artificial intelligence: A call for research on inequalities and structural change. *Socius*, *7*, 2378023121999581.

Kamaswaren, V., Cameron, L., Dillahunt, T. (2018). Support for Social and Cultural Capital Development in Real-time Ridesharing Services. *Computer-Human Interactions. CHI 2018: ACM Conference on Human Factors in Computing Systems.*

Kaplan, D. (November 7 2023). DC and DoorDash give free dashcams to delivery drivers. *Fox 5.* Accessed on 30 July 2025 at https://www.fox5dc.com/news/dc-and-doordash-give-free-dash-cameras-to-delivery-drivers

Katz, L. F., & Krueger, A. B. (2019). The rise and nature of alternative work arrangements in the United States, 1995–2015. *ILR review*, *72*(2), 382-416.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366–410.

Kharpal, A. Uber Reportedly used secret software called "Hell' to track rival Lyft drivers. Published 13 April 2017, CNBC. Accessed: https://www.cnbc.com/2017/04/13/uber-lyft-hell-software-track-drivers.html

Kitchin, R., & Dodge, M. (2014). *Code/space: Software and everyday life.* MIT Press.

Koch, R. (1999). The 80/20 principle: The secret to achieving more with less. Crown.

Korczynski, M. (2001). The contradictions of service work: call centre as customer-oriented bureaucracy. *Customer Service: empowerment and entrapment*, 79-101.

Locke, K. (2001). *Grounded Theory in Management Research.* Sage Publications.

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612.

Leidner R (1993) *Fast food, fast talk: Service work and the routinization of everyday life*. University of California Press.

Leonardi, P., & Treem, J. W. (2020). Behavioral Visibility: A New Paradigm for Organization Studies in the Age of Digitization, Digitalization, and Datafication. *Organization Studies*.

Levy, K. (2023). *Data driven: truckers, technology, and the new workplace surveillance*. Princeton University Press.

Macpherson, C. B. (1962). *The political theory of possessive individualism: Hobbes to Locke*. Oxford: Clarendon Press.

Maffie, M. (2022). The Perils of Laundering Control Through Customers: Conflict and Resistance in the Ridehail Industry. *Industrial & Labor Relations Review*.

Manriquez, M. (2019). Work-games in the gig-economy: a case study of Uber drivers in the city of Monterrey, Mexico. In *Work and labor in the Digital Age* (pp. 165-188). Emerald Publishing Limited.

Mayberry, K., Cameron, L. & Rahman, H. (2023) "Unhooking from the Matrix: The Rise of Algo-Activism" Routledge Handbook in the Future of Work. Bristol, UL.

McMillan Cottom, T. (2020). Where platform capitalism and racial capitalism meet: The sociology of race and racism in the digital society. *Sociology of Race and Ethnicity*, *6*(4), 441-449.

Möhlmann, M. (2021). Algorithmic nudges don't have to be unethical. *Harvard Business Review*, *22*.

Mollick, E. & Rothbard, N. (2014). Mandatory Fun: Consent, Gamification and the Impact of Games at Work. The Wharton School Research Paper Series.

Noble, S. U. (2018). Algorithms of oppression. In *Algorithms of oppression*. New York university press.

O'Brein, R. & Bensinger, G. (2017). Uber Faces FBI Probe on Targeting Rival Lift. *Wall Street Journal.* Accessed on 2 July 2024 at https://www.wsj.com/articles/uber-faces-fbi-probe-overprogram-targeting-rival-lyft-1504872001

O'neil, C. (2017). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

Occhiuto, N. (2017). Investing in independent contract work: The significance of schedule control for taxi drivers. *Work and Occupations*, *44*(3), 268-295.

Orlikowski, W. J. (2007). Sociomaterial Practices: Exploring Technology at Work. *Organization Studies*, *28*(9), 1435–1448.

Orlikowski, W. J., & Scott, S. V. (2015). The Algorithm and the Crowd: Considering the Materiality of Service Innovation. https://dspace.mit.edu/handle/1721.1/96870

Parrot, J. & Reich, M. (2024). Transportation Network Company Driver Earnings Analysis and Pay Standard Options. Accessed on 2 July 2024 at

https://irle.berkeley.edu/publications/report/transportation-network-company-driver-earnings-analysis-and-pay-standard-options/

Parrot, J., Reich, M., Yang, X. (2024). *The Economic Situation of TNC Drivers in Minnesota.* LERA 75th annual conference. New York, New York.

Pfeffer, J., & Baron, J. N. (1988). Taking the workers back out: Recent trends in the structuring of employment. *Research in organizational behavior*, *10*(1988), 257-303.

Pratt, M. G., & Bonacio, S. (2016). Qualitative Research in I-O Psychology: Maps, Myths, and Moving Forward. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 9*(4), 6933-715.

Rahman, H. A. (2021). The Invisible Cage: Workers' Reactivity to Opaque Algorithmic Evaluations. *Administrative Science Quarterly*, *66*(4), 945-988.

Rahman, H. (2024). *Inside the invisible cage: How algorithms control workers*. Univ of California Press.

Rahman, H., Karunkaran, A., & Cameron, L. (2023). Taming Platform Power: An Integrative Framework for How to Hold Multi-Sided Platforms Accountable. *Academy of Management Annals.*

Rahman, H. A., Weiss, T., & Karunakaran, A. (2023). The experimental hand: How platform-based experimentation reconfigures worker autonomy. *Academy of Management Journal*,

Ravenelle, A.J. (2017) Sharing economy workers: selling, not sharing, *Cambridge Journal of Regions, Economy and Society*, Volume 10, Issue 2, Pages 281–295,

Ravenelle, A.J. (2018). The New Entepreneur: Worker Experiences in the Sharing Economy.

Ravenelle, A. J. (2019). *Hustle and Gig: Struggling and Surviving in the Sharing Economy*. University of California Press.
Reid 2015

Ravenelle, A. J., Janko, E., & Kowalski, K. C. (2022). Good jobs, scam jobs: Detecting, normalizing, and internalizing online job scams during the COVID-19 pandemic. *New media & Society*, *24*(7), 1591-1610.

Rogoway, M. (2020). *Major Tech Company Using Facial Recognition to ID Workers*. GovTech. https://www.govtech.com/public-safety/Major-Tech-Company-Using-Facial-Recognition-to-ID-Workers.html

Rosenblat, A. (2018). *Uberland: How Algorithms are Rewriting the Rules of Work*. University of California Press.

Rosenblat, A. & Stark, L. (2016). Uber's Drivers: Information Asymmetries and Control in Dynamic Work. *International Journal of Communication*, *10*(27).

Rosenthal, P. (2004). Management Control as an Employee Resource: The Case of Front-line Service Workers. *Journal of Management Studies, 41*(4), 601–622.

Rynes, S. & Bartunek, J. (2015). It Just Keeps Getting More Interesting. In Elsbach, K. D. & Kramer, R. (eds.), *Handbook of Qualitative Organizational Research*. Routledge.

Scheiber, N. (2017). How Uber Uses Psychological Tricks to Push Its Drivers' Buttons. *The New York Times*. https://www.nytimes.com/interactive/2017/04/02/technology/Uber-drivers-psychological-tricks.html

Schor, J. B., Attwood-Charles, W., Cansoy, M., Ladegaard, I., & Wengronowitz, R. (2020). Dependence and precarity in the platform economy. *Theory and society*, *49*(5), 833-861.

Schor, J. (2021). *After the gig: How the sharing economy got hijacked and how to win it back*. University of California Press.

Shapiro, A. (2018). Between autonomy and control: Strategies of arbitrage in the "on-demand" economy. *New Media & Society*, *20*(8), 2954–2971.

Shestakofsky, B. (2017). "Working Algorithms: Software Automation and the Future of Work." *Work and Occupations* 44(4):376-423.

Shevchuk, A., Strebkov, D., & Davis, S. N. (2019). The Autonomy Paradox: How Night Work Undermines Subjective Well-Being of Internet-Based Freelancers. *ILR Review*, *72*(1), 75–100.

Shu, C. (2017). Uber reportedly tracked Lyft drivers using a secret software program "Hell." *TechCrunch.* Accessed on 2 July 2024 at https://techcrunch.com/2017/04/12/hell-o-uber/

Small, M. L., & Calarco, J. M. (2022). *Qualitative literacy: A guide to evaluating ethnographic and interview research*. Univ of California Press.

Spreitzer, G. M., Cameron, L., & Garrett, L. (2017). Alternative Work Arrangements: Two Images of the New World of Work. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*(1), 473–499.

Streeter, T. (2015). Steve jobs, romantic individualism, and the desire for good capitalism. *International Journal of Communication, 9,* 3106–3124.

Taylor, B. (May 30 2024). Lyft driver sues company after being abducted. *Click 2 Houston.* Accessed on 30 July 2025 at https://www.click2houston.com/news/local/2024/05/30/lyft-driver-sues-company-for-1m-after-being-abducted-sexually-assaulted-by-armed-rider-with-long-criminal-history/

Thelen, K. (2018). Regulating Uber: The politics of the platform economy in Europe and the United States. Perspectives on Politics, 16(4), 938-953.

Thorp, A. A., Healy, G. N., Winkler, E., Clark, B. K., Gardiner, P. A., Owen, N., & Dunstan, D. W. (2012). Prolonged sedentary time and physical activity in workplace and non-work contexts: A cross-sectional study of office, customer service and call centre employees. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 128.

Ticona, J. (2022). Red flags, sob stories, and scams: The contested meaning of governance on carework labor platforms. *New Media & Society*, *24*(7), 1548-1566.

Tolentino, J. (2017). The gig economy celebrates working yourself to death. *The New yorker*, *22*

Vallas, S., & Schor, J. B. (2020). What Do Platforms Do? Understanding the Gig Economy. *Annual Review of Sociology*, *46*(1).

Van Maanen, J. (1991). The smile factory: work at Disneyland. *Organizational Culture,* Sage.

Van Maanen, J., & Barley, S. (1984). Occupational Communities: Culture and control in organizations. *Research in Organizational Behavior*, *6*, 287–365.

Wang, X. & Reger, R. K. (2017). Rolling the Dice: What Methodological Choices Maximize Chances for Publication in Premier Strategic Management Journals? In Galavan, R., Sund, K. and Hodgkinson, G. (eds.), *Methodological Challenges and Advances in Managerial and Organizational Cognition* (*New Horizons in Managerial and Organizational Cognition, Vol. 2*). Emerald Publishing.

Watkins, E. A. (2021). *The Polysemia of Recognition: Facial Recognition in Algorithmic Management*. [Doctoral dissertation.] Columbia University.

Watkins, E. A. (2022). "Have you learned your lesson?" Communities of practice under algorithmic competition. *New Media & Society*, *24*(7), 1567-1590.

Watkins, E. A. (2023). Face Work: A Human-Centered Investigation into Facial Verification in Gig Work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1-24.

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society*, *33*(1), 56–75.

Wood, A. J., & Lehdonvirta, V. (2021). Antagonism beyond employment: how the 'subordinated agency' of labour platforms generates conflict in the remote gig economy. *Socio-Economic Review*, *19*(4), 1369-1396.

Woodcock, J., & Graham, M. (2019). The gig economy. *A critical introduction. Cambridge: Polity*.

Wong, J. (2017). Greyball: How Uber Used Secret Software to Dodge the Law. *The Guardian*. Accessed at https://www.theguardian.com/technology/2017/mar/03/uber-secret-program-greyball-resignation-ed-baker

Youshaei, J. (2015, February 4). The Uberpreneur: How an Uber drivers makes $252,000 a year. *Forbes*. Retrieved from https://www.forbes.com/sites/jonyoushaei/2015/02/04/the-uberpreneur-how-an-uber-driver-makes-252000-a-year/#650040004e8e.

Zuboff, S. (2019). *The Age of Surveillance capitalism: The Fight for a Human Future at the New Frontier of Power*. Profile Books.

EXHIBIT C - PRIOR EXPERT TESTIMONY

1. 2019. Testimony provided for hearing held by the Pennsylvania State Senate Democratic Policy Committee
2. 2021. Testimony provided for hearing held by the Pennsylvania State Senate Democratic Policy Committee
3. 2021. Gachie v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Houston, TX; Deposition and Arbitration
4. 2021. Omey v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Houston, TX; Arbitration
5. 2021. Chitambira v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Dallas, TX; Arbitration
6. 2022. Barysas v. Uber Technologies, Inc; plaintiff; Houston, TX; Arbitration
7. 2024. Andrea Joy Campbell, in her official capacity as Attorney General for the Commonwealth of Massachusetts v. Uber Technologies, Inc. and Lyft, Inc.: plaintiff; Boston, MA; Deposition and Trial
8. 2025. Attorney General of Minnesota v. Shipt, Inc., Fourth Judicial District; plaintiff; Philadelphia, PA, Deposition.

EXHIBIT 2

Expert Report

prepared by Lindsey D. Cameron, Ph.D.

October 12, 2023

I. Purpose of the Report

1. I have been asked by the Office of the Attorney General of the Commonwealth of Massachusetts (hereinafter "Attorney General") to provide expert testimony in this matter.

2. I have been asked by counsel for the Attorney General to do the following:
    a. Provide an overview of organizational control and algorithmic management as it applies to on-demand[1] organizations. (Section III)
    b. Apply organizational theories on if, and if so how, on-demand companies execute organizational control over their workers. (Sections IV)
    c. Apply organizational theories on if, and if so how, ride-hailing companies execute organizational control over their workers. (Sections V)
    d. Provide an overview of narratives used by ride-hailing and on-demand companies to influence drivers and other stakeholders. (Sections VI)
    e. Assess whether, and if so how, Uber Technologies, Inc., (hereafter "Uber") and Lyft, Inc. (hereafter "Lyft") implement organizational control, as defined by the literature on organizational theory and behavior.

3. As explained below, my opinion is that Uber and Lyft deploy organizational control through their algorithmic management systems and that this form of control is integral to their business model and is evident in their relationship with their drivers. My opinion is also that Uber and Lyft also deploy certain narratives to influence drivers' behavior. The basis for my opinion is summarized below. I may revise my opinions further as additional information becomes available to me. I reserve the right to supplement this report.

[1] An on-demand organization is an organization that relies on a digital infrastructure to connect workers with customers for short-term assignments in real time—hence the term, "on-demand." (Cameron, 2022:2).

II. Qualifications of the Author

4. I am an assistant professor of management at the Wharton School of the University of Pennsylvania in Philadelphia, PA. I also hold a courtesy appointment in sociology at the University of Pennsylvania and I am a member (fellow) of the Institute of Advanced Studies, Princeton. I am a faculty associate at the Harvard Law School's Berkman Klein Center for Internet and Society and a former fellow of the Data and Society Research Institute in New York City.

5. At Wharton, I teach an executive course on the Future of Work and a graduate (MBA) class on managing emerging enterprises, such as on-demand companies and technology start-ups. I also teach several doctoral classes on qualitative methods and work and employment relations with a focus on the on-demand economy. At the University of Michigan, I taught a class on organizational behavior and organizational effectiveness. I was asked to give remarks to the Joint Task Force on Misclassification of Employees hosted by the Department of Labor, Commonwealth of Pennsylvania, titled "How Digital Platforms are Reconfiguring Work." I have also presented my research in two public hearings held by the Pennsylvania State Senate Democratic Policy Committee on issues relating to algorithmic management, the on-demand economy, and worker classification.

6. Prior to Wharton, I received an undergraduate degree (S.B.) in electrical engineering and computer science with a minor in French from Harvard University in Cambridge, MA in 2005. I received a master's (M.S.) in engineering management, with a focus on crisis, risk, and emergency management, at the George Washington University in Washington, DC in 2009. I was a Provost Fellow at the Wharton School, University of Pennsylvania from 2017-2018. I received a Ph.D. in management from the University of Michigan in Ann Arbor, MI in 2020. All my education has included significant research training and I have completed advanced training in quantitative and qualitative methodology, leadership, and Arabic at the University of Maryland in College Park, MD, the Maryland Institute of Integrative Health, in Laurel, MD, and the American University of Cairo in Cairo, Egypt, respectively. I have been at the University of Pennsylvania since completing my Ph.D. In addition, I spent twelve

years working at the National Security Agency (NSA) and Central Intelligence Agency (CIA) as a data and intelligence analyst.

7. As an organizational and management scholar, my research is grounded in the disciplines of psychology and sociology. My research program is primarily qualitative and draws on the norms and standards of qualitative methodology in the organizational management field which emphasizes in-depth immersion and observation – to see things from the experiential point of view of actors in the field (e.g., Charmaz, 1996; Glaser & Strauss, 1967; Locke, 2001; Bechky & O'Mahoney, 2015). Hallmarks of qualitative research include long-term (participant) observation, longitudinal interviews, and in-depth analysis of archival documents, such as company materials or web forum postings. Qualitative methods are especially useful for studying emerging phenomena, such as the on-demand economy, because they allow for an in-depth examination of mechanisms and processes. Moreover, research using qualitative methods is among the most impactful, highly cited, and ground-breaking in the field of organizational management, evident in the numbers of awards and citations, as compared to studies that use other research methods (Wang & Reger, 2017; Pratt & Bonacio, 2016; Bartunek, Rynes, & Ireland, 2006; Rynes & Bartunek, 2015; Bansal and Corley, 2011).

8. As an organizational and management scholar, my research is grounded in the disciplines of psychology and sociology. My research program focuses on algorithmic management and on-demand organizations. Given the emerging phenomena, I primarily employ qualitative methods (e.g., participant observation, interviews, document review) that are particularly well-suited for novel phenomena. As a "structural ethnographer" (Burawoy, 2017), my approach to research is worker-centered, seriously considering workers' experience in my analysis to develop broader claims about social structures and processes. I take a granular understanding of how the work is done—examining the interactions between the worker, the organization, and the customers—and I collect data via immersion and comparative work. This approach is rare, even among ethnographers, both because of the difficulty in gaining research access and its time-consuming nature—but it is important. Through immersion, I

gain in-depth exposure to how the work process unfolds and, by comparing across settings (workers, on-demand organizations, cities, countries), I can identify mechanisms that cut across said settings. Moreover, it allows me to link the micro—the individual workers' actions—to the macro—sociocultural structures and processes. Together, my methods and data enable me to inductively discover and conceptualize theories that closely reflect the nature of algorithmic management and on-demand work.

9. My academic research is on algorithmic management, with an emphasis on the on-demand economy (colloquially called the "gig economy"). In particular, my research program focuses on how algorithmic management shapes organizational structure and processes and how these changes affect workers with an emphasis on the interplay between organizational control and worker autonomy. Since 2016, I have spent the past seven years researching the on-demand economy, with my research including, studying workers on Uber, Lyft, Via, Instacart, TaskRabbit, DoorDash and Amazon Flex, among others, in over eight countries. My data collection includes participation observation (i.e., working in the on-demand economy, being a customer of on-demand services, and observing at organizing units), interviews, focus groups, archival analysis (e.g., web forums, video logs, and document reviews), surveys, and collecting financial diaries. One core finding across my research is how algorithmic management can seemingly grant autonomy, or a sense of choice, to workers, yet this autonomy is illusory because workers' autonomy is confined to the narrow choices afforded by the management system (Cameron 2020, 2021, 2023; Cameron & Rahman, 2022).

10. My research on the ride-hailing industry includes the following data. I spent approximately one hundred hours applying for, training, and working as a ride-hailing driver for Uber in the Washington, DC metro area. A research assistant, trained by me, also drove and collected research data in the Detroit metro area. During this time, I conducted in-depth interviews with drivers about their work routines and career histories. In total I conducted more than 150 in-depth semi-structured interviews (n=63 drivers in North America interviewed over multiple years for a total of 138 interviews with drivers; the remaining interviews were with customers), as well as conversational interviews (n=112 drivers) while riding as a participant

observer. I also reviewed public documents by and about Uber, fielded surveys and financial diaries with ride-hailing drivers and spent time on driver forums and at organizations focused on drivers' rights. I have published numerous articles, several award-winning, based on this qualitative and quantitative data, some of which I cite within, (Cameron, 2020; Cameron & Rosenblat, 2020; Cameron, 2021; Cameron, 2022; Cameron & Rahman, 2022; Cameron & Meuris, 2022; Kamaswaren, Cameron & Dillahunt, 2018; Mayberry, Cameron & Rahman, 2023) as well as integrative review pieces (Spreitzer, Cameron, Garrett, 2017; Rahman, Karunkaran & Cameron, 2023; Cameron, Lamars, Leicht-Deobald, Lutz, Meijerink, & Mohlmann, 2023). In addition, I have studied the experience of ride-hailing drivers internationally. Outside of North America, my ride-hailing datasets include interviews with drivers (n=181), field notes from observations (n = 54), forum data, and participants' artifacts. In addition to the ride-hailing industry, my research examines the implications of algorithmic management in other on-demand economy companies, such as Instacart, DoorDash, and TaskRabbit, and includes a large corpus of interviews (n=224), participant artifacts (n=125), and archival documents (see Cameron, Thomason & Conzon, 2021; Mayberry, Cameron & Rahman, 2023; Cameron, Chan & Anteby, 2022; and Sprietzer, Cameron, & Garrett, 2017 for examples).

11. I have written multiple academic papers that have been published in several leading management, sociology, psychology, and information systems journals, including *Organization Science, Journal of Applied Psychology, Organizational Behavior and Human Decision Processes, Academy of Management Annals, Annual Review of Organizational Psychology and Organizational Behavior, Communications of the Association of Information Systems, Communications of the Association of Information System, and Computer-Human Interactions of the Association of Computing Machinery.* (See references for citations.) I am a reviewer at several leading management, sociology, and labor relations journals, including *Administrative Science Quarterly, Academy of Management Journal, American Sociological Review, Organization Science, Socio-Economic Review, Industrial Labor Relations, Sociological Perspectives,* and *Work and Occupations*, and funding institutions, such as the National Science Foundation. I am on the editorial board of *Socio-Economic Review*, a leading organizational sociology journal. I have presented my research on algorithmic

management and the on-demand economy in numerous public forums and academic settings, including the Ford Foundation, Aspen Institute, Microsoft, Harvard Law School, Harvard Business School, Stanford Business School, Stanford University's School of Engineering, Massachusetts Institute of Technology, London Business School, Peking University, and the University of Chicago. My research on the on-demand economy has been featured in national and international outlets, such as Washington Post, NPR's Marketplace, CNBC, Kiplinger's, Forbes, and the World Economic Forum, and has won twelve (12) national and international awards.

12. I have carefully read and considered information provided to me by the Attorney General's office to form this opinion. These materials about Uber and Lyft, which are similar in nature to what I typically review in my research about algorithmic management and organizational structure in the on-demand economy and ride-hailing, provided the basis for my opinion in this case.

13. A list of other cases in which I have testified as an expert by public hearing, trial, or deposition is attached in **Appendix A**. I am being compensated at the rate of $400 per hour. My compensation is not dependent on this opinion or the outcome of this litigation.

III. How Organizational Scholars Define Organizational Control and its Importance

14. As an organizational and management scholar researching the on-demand economy and on-demand organizations, a major focus of my research is on organizational control. Control is one of an organization's primary functions (Fayol 1949) and the "most fundamental problem" (Van Maanen & Barley 1984: 290) they face. The challenge is that organizations must obtain cooperation among individual workers who share only partially congruent goals with the organization, thus organizations must attempt "to increase the probability that individuals will behave in ways that will lead to the attainment of organizational objectives" (Flamholtz, Das, & Tsui 1985). In the management and organizational literature, organizational control is defined as any process that aligns an individual worker's

"capabilities, activities, and performance with the organization's goals and aspirations" (Cardinal, Sitkin, & Long 2004: 411).

15. Conceptually, there are two dimensions of organizational control: general and detailed (Edwards, 1986). General control refers to the overarching "accommodation of workers to the overall aims of the enterprise" (Edwards, 1986: 6) and can include broad organizational processes such as hiring, socialization, or how bureaucratic structures shape information flow. In contrast, detailed control refers to the organization's control over the execution of the work itself, including the pace of work, allocation of tasks, performance evaluations, and discipline. Organizations must balance general and detailed control measures in order to maintain a motivated workforce and ensure profitability (Friedman, 1977). In other words, over-prescribing elements of detailed control (for example, how long workers on the assembly line can go to the bathroom) may undermine general control in that workers may become disgruntled. Thus, organizations tend to rely on incentives or "carrots" more than punishments or "sticks" so that workers align their efforts with managerial objectives and goals.

16. Organizational control is critical for any organization because it ensures that workers' efforts are aligned with managerial goals and objectives. Organizational control is especially important for on-demand companies. First, on-demand companies often consider their workforce to be independent contractors. As such, to elicit these workers' participation, on-demand organizations rely on algorithmic management systems and customer control. But these practices, which distance the organization's control practices from its workers, often obfuscate the organization's actual relationship with workers, in essence, laundering control.[2] Second, the organizational strategy of most on-demand companies is to secure market dominance before achieving profitability.[3] For on-demand organizations, capturing market share means that they must attract a significant customer base and, correspondingly, workers

[2] Classification is especially relevant in closed labor market platforms, such as Uber, Lyft, and Instacart, in which algorithmic management much more heavily directs and controls workers' actions, as opposed to open labor market platforms, such as TaskRabbit and Upwork.

[3] This process is also referred to as achieving a "network effect," where the value of the on-demand company increases based on the number of people who use that product or service increases (Rahman, Karunkaran & Cameron, 2023; Cusamon, Gawer & Yoffie, 2019).

to serve this customer base to ensure that services are delivered 'on-demand.' In practice, this manifests as a set of organizational practices and policies to try and keep customers satisfied (i.e., a customer-centric business model) and to try to get workers on the app, available to work, especially during high-demand periods (i.e., via algorithmic management systems, directives, and nudges to influence workers' behaviors). Moreover, on-demand organizations will often regularly experiment on their workers and customers, testing out new products and features, to inform potential strategic choices (Rahman et al., 2023). Taken together (and as explained in greater detail below), these two factors help explain why getting organizational control 'right' is so crucial for on-demand organizations—it is both pivotal to on-demand companies' quests for market dominance and must also be obscured to a large majority of its workers.

IV. How On-Demand Organizations Exercise Organizational Control through Algorithmic Management

17. Algorithmic management systems are "a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process" (Duggan et al., 2020: 119). Deeply intertwined with society, algorithmic management systems are what science and technology studies scholars call *sociotechnical*, a term that calls attention to how values, institutional practices, and inequalities are embedded into the code, design, and use by the authors of the code. Thus, algorithmic management systems reflect and embody broader socio-cultural values and can never be seen as socially or politically neutral or "just a tool" (Orlikowski, 2007; O'Neill, 2006; Joyce et al., 2021). In the remainder of this report, I explain the sociotechnical features—the values, institutional practices, and inequalities—that are embedded within the algorithmic management system of Uber and Lyft. As I explain, Uber and Lyft have designed their algorithmic management systems, to exercise ever-increasing organizational control over workers' behaviors while also obfuscating the companies' intent and inherent power in the platform-worker relationship.

A. Four Components of Algorithmic Management That Lead to an Intensification of Organizational Control

18. Like traditional organizations, on-demand organizations rely on a combination of general and detailed control to align workers' behaviors and efforts with organizational goals and objectives. Unlike traditional organizations which rely on human managers to implement control, on-demand organizations rely on algorithmic management systems. Under these algorithmic management systems, algorithms, rather than human managers, perform managerial tasks such as hiring, evaluating, and rewarding/disciplining workers (Lee et al. 2015; Danaher 2016; Rosenblat 2018; Shapiro, 2018; Wood et al., 2019; Cameron 2020; Kellogg et al. 2020; Schor 2020; Vallas & Schor 2020).[4] As explained below, these algorithmic management systems control workers' behaviors through organizational design, continuous surveillance, swift punishments, and the effective deployment of incentives and nudges (Thelen, 2018; Mohlmann et al., 2021; Rahman, 2021). While all organizations, to some extent, exercise control over their workers, the algorithmic management system that the on-demand business model relies upon is even more "comprehensive, instantaneous, interactive, and opaque" (Kellogg et al. 2020: 366) than other management systems, resulting in an unprecedented quantification and intensification of organizational control over workers. Some scholars have gone as far to call the control exercised by on-demand organizations as an "invisible cage" because they implement a form of organizational control in which the criteria for success are largely invisible to workers and changes to those criteria are unpredictable, made solely by the organization itself (Rahman, 2021).

19. Several features contribute to algorithmic management systems' quantification and intensification of control. First, algorithms are engineered by organizations to use quantified metrics to comprehensively monitor and track workers' minute movements. Embedded in cameras, biometrics trackers, and sensors, algorithms record workers' physical movements to prove adherence to the rules and regulations of the organization, such as by verifying worker identities (e.g., Rogoway 2020; Zuboff 2019), tracking drivers' location (Levvy, 2022;

[4] While some organization may use algorithms, alongside human managers, as part of their management system (e.g., hiring, see Ajunwa, 2023 for a review) this is distinct from algorithmic management systems which are more comprehensive in which algorithms perform (nearly) all managerial functions.

Viscelli, 2018), acceleration rate and braking speeds for workers operating motor vehicles (Clemes et al. 2014; Thorp et al. 2012), and monitoring emails to assess mood and productivity (Goldberg et al. 2016; Leonardi & Treem 2020). In ride-hailing, telemetrics monitor workers' driving activity (e.g., location and braking speeds) which can then be inputted into an algorithmic management system. And photo verification systems verify drivers' identities and ensure compliance with system rules, such as wearing masks during the COVID-19 pandemic (Watkins 2021, 2023).

20. Second, algorithms are designed to collect data from the organization's workers and feed that information back into the algorithmic management system, allowing the system to improve its own efficiency by increasing managerial knowledge and organizational control over workers. On-demand organizations are customer service organizations, in that they facilitate exchanges between customers and workers. "The customer is king" is a common refrain among service organizations, emphasizing their mission to prioritize customer satisfaction. Indeed, many functions performed by the algorithmic management system are meant to do exactly that, prioritizing customers over workers. For example, on-demand companies, such as TaskRabbit and Upwork, can change how search results of worker profiles are presented to customers based on real-time feedback from customer comments, number of page views, and worker performance (Alkhatib & Bernstein 2019; Gillespie 2018). The changes allow the company to increase the probability of a successful match between customers and workers, satisfying customers' needs, and ultimately, keeping and attracting their customer base. Often, workers are unaware of the changes accomplished by the algorithmic management system and their implications for their economic livelihood (Irani & Silberman, 2013; Rahman, 2021). In ride-hailing, companies can, and often do, instantly suspend drivers' access to the app or assign them a less profitable ride after a customer complaint, doing so even before the complaint is investigated, and the driver has an opportunity to present their own version of events (Cameron, 2022). Such actions favor the customer over workers, supporting the on-demand organization's customer-centric business models. On-demand organizations can collect information about workers whether they are logged into the app and use this information to optimize their own operations and/or to try to influence workers' and

customers' behaviors in some way. Ultimately, on-demand organizations rely on worker data for their business model to work.

21. Third, algorithmic control is more interactive than previous forms of organizational control because algorithms enable interactive participation from multiple parties in different locations and on-demand organizations can use this information to run experiments. On-demand apps, for example, allow workers to compete across multiple zones for assignments and communicate in real-time with customers (Shevchuk et al. 2018). This often results in workers staying on-line to work on the app at strange hours which is precisely one of the goals of an on-demand organizations—to have an always available, on-demand workforce (Schor et al., 2020; Cameron, 2023). Moreover, on-demand companies have collected data about their workers' activities on competitors through third-party analytics services (Isaac, 2017; Isaac & Lohr, 2017; Isaac, 2019).

22. Many on-demand organizations run experiments on their workers, to which workers are invisible to, pertaining to various aspects affecting work conditions, including changing their visibility in algorithmically mediated search results, how workers' profiles are presented to customers, giving feedback about their ratings, or giving automated communications to deter certain behaviors (Rahman, Weiss & Karunkaran, 2023). Workers are often unaware of the specifics of the experiments that are being run on them.

23. How these experiments are run are based on whether the on-demand organization is an open-labor market platform and closed-labor market platform. In open-labor market platforms, such as Upwork and TaskRabbit, customers and workers choose one another, often from an algorithmically curated list, to work on a mutually agreed upon tasks. By contrast, in closed-labor market platforms, such as Uber, Lyft, and Instacart, the organization's algorithmic management system matches customers and workers to complete specified-tasks.

24. On open-labor platforms, the platform company experiments with how workers' ratings are calculated, how prominently ratings are displayed to workers (if at all), and how they match

customers with workers (Rahman et al., 2023; Ticona & Matescu, 2020). In these instances, particularly where there is a robust on-line community, workers know they are "guinea pigs", but are generally unaware of the experiments' specific terms (Rahman et al., 2023). By contrast, because ride-hailing is a closed labor market platform, companies can automize drivers and routes at the city-level, in ways that are unobservable to drivers. Often workers in closed labor platforms are either unaware that there are experiments, in general, or of the specifics of any experiment (e.g., the terms, their role, the results, how their data is being used to nudge their behaviors in even more complex ways). Author of *Uberland: How Algorithms are Rewriting the Rules of Work* states, "Because drivers don't really expect to be the subjects of A/B testing, such as when the company tests one version of an app feature on some drivers and another version on other drivers to evaluate which one preforms better: the experimental practices that might work on everyday consumers on the Internet have different consequences in the workplace at Uber" (Rosenblat, 2018:15).

25. Moreover, given that work on closed labor market platforms is generally completed in-person, these workers are less likely to be active in on-line communities that would promote information sharing among themselves (Cameron, 2022). This lack of visibility makes it impossible for drivers to effectively compare the details of their rides they perform (types, fare amounts, speed of matching) to those being assigned to their fellow drivers, leaving them to question the integrity of the algorithmic management system (Cameron, 2022). In the face of unknowable experiments, workers often rationalize their diminished autonomy as a "business as usual" aspect of work life on the platform (Rahman et al., 2023).

26. Fourth, algorithms are often more opaque than previous forms of organizational control because the data and algorithms used to control workers are usually proprietary and undisclosed (Burrell 2016; Orlikowski & Scott 2014). And even if individuals had the ability to examine the algorithmic code, such information would likely be indecipherable (Noble, 2018; Christin, 2020). This opacity promotes an information asymmetry between workers and the organization, as workers are unaware of what data is being collected and how the on-demand company uses worker-related data to make decisions that affect them (Rosenblat & Stark 2016). For example, drivers are unaware if and/or how customer ratings and telemetric

scores may affect future rides offered to them, leaving drivers completely surprised when they are suspended from the app (Cameron, 2022).

27. These four components of algorithmic management systems—quantification of metrics, instantaneous feedback, their interactive nature, and opaqueness—lead to a quantification and intensification of organizational control in on-demand organizations as compared to other organizational forms (Aneesh, 2009; Kellogg et al., 2020; Vallas & Schor, 2020). By capturing fine-grained data about workers and customers, on-demand organizations can more effectively design a management system that more effectively "captures" (Noble, 2018) workers' attention and nudges them into making decisions that are in alignment with organizational goals. Algorithmic nudges can be quite persuasive in guiding worker behavior. Möhlmann (2021:1) notes, "with so much data about workers' behavioral patterns at their fingertips, companies can now develop personalized strategies for changing individuals' decisions and behaviors at a larger scale. These algorithms can be adjusted in real-time, making the approach even more effective." Remarking on the effectiveness of the algorithmic management system and the market dominance of Uber, Iwan Barankay, an economist at the Wharton School, aptly summarized this degree of organizational control, explaining that "Whatever Uber does, they can get away with it because there's very little push back from the other side. Much of the inner-working of these management systems are obscured from workers, such that they are unaware to the extent of which the power and information of the worker-platform company relationships is biased toward protecting the interests of the platform and customers over workers (Chai & Scully, 2020).

B. How On-Demand Organizations Exercise Organizational Control Through Algorithmically Mediated Customer Control

28. On-demand organizations are customer service organizations. In these type of organizations, frontline workers are essential to the organizations' desire to satisfy customers because they directly interact with the organizations' customers regularly (Leidner 1993, Batt 1999,

Korczynski et al. 2000). To ensure that service workers behave in ways that are consistent with the organization's objectives, organizations curate workers' behavior through "service rules" and "feeling scripts" in which certain behaviors are emphasized, such as cheerfulness for Disneyland Park attendants or friendliness for flight attendants (Van Maneen 1991; Hoschild 1983). When these rules are violated, workers can receive poor evaluations and face sanctions, such as being forced to take remedial training, being transferred to lower-paid "back stage" work, or even being terminated.

29. While service organizations have always used customers to monitor workers, such as through mystery shoppers, on-demand organizations are unique in the extent to which they outsource performance management to customers and use algorithmic management to collect that data and then influence worker behavior. Highlighting the prominence of customers in service organizations, Fuller and Smith (1991) describe customers "as agents in the management circuit" such that "customers, rather than managers, are […] the ones who must be pleased, whose orders must be followed, whose ideas, whims and desires appear to dictate how work is performed. (11)" In on-demand organizations, this outsourcing of organizational control to customers is so complete that scholars describe it a "laundering control" (Maffie, 2022) because customers, ostensibly, are the ones evaluating workers when it is actually the on-demand organization that is directing and controlling the entire labor exchange and then using the results for its own business purposes. Guidelines—posted on on-demand companies' websites, Youtube channels, and Instagram feeds—offer suggestions of appropriate behaviors. As part of Instacart's official communication materials, for example, the company presents "shoppers," i.e. the company's on-demand workers, with characteristics of ideal shoppers, such as asking customers for replacement items when something is out of stock and sending customers updates on their location and order progress (Cameron et al., 2022). Workers reported being so pressured by these suggestions that they would take on additional physical risk during dangerous events, such as the COVID-19 pandemic, to keep customers satisfied (Cameron, Thomson & Conzon, 2021).

30. On-demand organizations integrate customer control into their algorithmic management systems. They match workers with customers and compute workers' overall evaluation

scores and they outsource the task-by-task monitoring and evaluation of interactions to customers (Shapiro 2017, Wood et al. 2019). In algorithmically mediated customer control, these companies use "customers as an additional layer of managerial control by empowering customers to direct, monitor, and/or evaluate workers" (Maffie 2020, pg. 5). The algorithms then track these ratings, computing an overall score for workers that then affects workers' access to future work assignments (Rosenblat 2018, Ravenelle 2019, Schor et al. 2020; Cameron & Rahman, 2022). Workers with lower ratings, for instance, may have lower visibility in platforms' search results, be matched more slowly to incoming assignments, or lose access to the platform (Leung 2014; Pallais 2014; Rahman 2021). Customers and workers cannot see the ratings and feedback that each party provides about the other until both parties complete the feedback process and, at times, may not be able to assign a rating to a specific interaction. Although workers rate customers, in practice, these ratings are largely meaningless, as workers often state they universally give customers perfect ratings to signal to future customers that they are easy to work with and to keep the work process functioning smoothly (i.e., not wanting to spend extra time providing feedback for a sub-five star ride; Cameron & Rahman, 2022; Cameron, 2020; Rahman, 2019).

31. How an on-demand organization exercises algorithmically mediated customer-control, and the visibility of its algorithmic management systems is dependent on if it is an open or closed labor market platforms. In open labor market platforms (e.g., TaskRabbit, Upwork), customers have full discretion to choose the freelancers to work on their projects; however, the app's matching algorithm facilitates this process in two ways (Leung, 2014; Rahman, 2021; Cameron et al., 2021). First, customers can enter keywords into the organization's search engine (e.g., "design a video game," "hang pictures") and/or use the filtering criteria (e.g., rating thresholds, location, earnings, experience) to refine their searches. Then the companies' matching algorithms present customers with a list of freelancers they can invite to apply for their job. Alternatively, customers can submit a project description and preferred freelancer qualifications (e.g., desired level of experience, skills required) and the matching algorithms will suggest freelancers to customers and projects to freelancers. Freelancers are free to work on multiple projects simultaneously, and customers can hire multiple freelancers to work on the same project. For on-demand companies like Upwork, for example, when a

project is done, the customer rates the worker on a scale of one to five along six dimensions—availability, communication, cooperation, deadlines, quality, and skills (Rahman, 2019). These ratings are highly visible and prominently displayed next to users' profile names in search results. Search results may also suggest specific freelancers to customers based on their ratings and offer incentives, such as bonuses or reduced commissions, based on their ratings. If workers' ratings fall below a certain threshold, they may no longer be featured in the search results. Moreover, algorithms or other technology monitor workers' behaviors, such as via automatic screenshots or keylogging, to ensure that workers are behaving in ways that are in alignment with the objectives of both the organization and the customer (Ajunwa, 2023).

32. As compared to open labor market platforms, in closed labor markets platforms (e.g., Uber, Lyft, and Instacart), algorithmic management is more deeply embedded into the labor process and more prominent for both workers and customers signifying a greater level of algorithmically mediated organizational control. Once workers have logged onto the app, they are algorithmically matched with tasks using a process that is not visible to workers (i.e., workers are unaware on the factors that match them with a given rides). Matches are meant to optimize the marketplace as a whole (Lee et al., 2015; Mohlmann et al., 2021). In ride-hailing, for example, a company's matching algorithm considers factors such as, customer ratings, physical proximity to the customer, acceptance and cancellation rates, routing, predicted demand near rider destination, vehicle and ride type requested (e.g., luxury rides) (Rosenblat, 2018). Yet because matching is set for network optimization, matches do not always prioritize individual workers' preferences.

33. In both open and closed labor markets, workers are often evaluated by customers on a five-point scale and/or telemetrics. In ride-hailing, for example, at the end of every ride, customers rate the ride, and the algorithm uses this rating to calculate an overall score based on the driver's ratings over a past set of rides (Cameron, 2020, 2023; Rosenblat, 2018). These ratings score help ensure that workers abide by on-demand companies service rules and scripts, in that workers exhibit behavior that is pleasing to customers. Ratings are highly visible, and workers can see them immediately upon logging into the app; however, workers

cannot see which specific customer provided which feedback (Cameron & Rahman, 2022). If ratings fall below a certain threshold workers can be asked to take remedial training and/or be blocked from logging into the app, which essentially equates to being fired. In Instacart, for example, shoppers may not be eligible to get shopping blocks during the most lucrative times if their ratings are not high enough (Cameron, Chan & Anteby, 2022). Algorithms and telemetrics monitor workers' behaviors, often via screenshots and gyromagnetic sensing, to ensure that workers behave in ways that are in alignment with the objectives of both the organization and the customer. Workers are sent warning messages and can be blocked from logging into the app if they do not meet the company's metrics and may lose access to preferential loyalty programs, such as Uber Pro and Lyft Rewards (Rosenblat, 2018; Cameron, 2020).

34. Because on-demand organizations rely heavily on customer feed-back, workers are particularly at risk of being penalized by the organization as a result of customers manipulating the ratings systems to their favor (Rahman, Karunkaran & Cameron, 2023; Maffie 2022; Ravenelle, 2019; Cameron & Rahman 2022). For example, many workers report being temporarily or permanently suspended from the app after a one-time complaint from an irate customer who was upset because they were not given preferential treatment or because a worker enforced a safety regulation. With a "customer is king" mindset, on-demand companies have been accused of taking customer reports at face value, without getting the worker's perspective on an event before sanctioning them. This is especially troubling given the increasing number of customers who have been caught falsifying reports to get free or reduced services or assuage a personal vendetta (Maffie, 2022; Grohmann et al., 2022). More generally, research shows that women and people of color disproportionately receive lower ratings than white males (Hannack et al., 2016; Rosenblat, 2018). If blocked from the app because of a customer complaint, workers have limited means of recourse to regain access through official channels (Cameron & Rahman, 2022; Price, 2018).

C. How Ride-Hailing Companies Use Algorithmic Management to Obfuscate Their Organizational Control of Workers

35. One way that organizations can avoid fueling worker resentment and resistance is to superficially provide workers with a sense of autonomy while also imposing significant constraints—that is, allowing for some worker discretion, within boundaries provided by the organization (Friedman 1977; Cameron, 2021). Wood and Lehdonvitra (2021) call this "subordinated agency." As I describe below, ride-hailing companies like Uber and Lyft are constantly balancing these tensions—directing workers' behaviors through algorithmic management systems, but not so much that drivers balk at the companies' goal of keeping drivers on the app. In this section I describe three practices that ride-hailing companies use to promote a false sense of autonomy for drivers on the app—constant and confined choice, gamification, and workplace games—each of which serve to further enmesh workers into the on-demand company's algorithmic management system of control.

36. *Constant and Confined Choice:* Algorithmic management scaffolds drivers work activities such that workers are afforded a set of constant and confined choices. The algorithmic management system provides a set of choices that are narrow, such as the choice to accept a ride, the choice to which rate a rider, and drivers can make hundreds of these choices within a short period of time. Workers' behaviors align with two dominant tactics (Cameron, 2020, 2023). In *engagement tactics,* drivers interact with the algorithmic management system within its boundaries: they make decisions about what rides to accept, when, where, and for which company to work for, and they usually adhere to nudges. In *deviance tactics*, by contrast, drivers manipulate the algorithmic management system by pushing against its boundaries: they decline certain rides and try to inflate fares to obtain desired rides, for example. These actions, if detected, are penalized, but the sanctions can often be easily countered (Cameron, 2020; 2023). While the behaviors associated with these two tactics are practical opposites, they both contribute to workers' sense of autonomy in part because workers perceive themselves as skillful in being able to navigate the algorithmic management system. Yet the reality is that the workers' choices are constrained, coming from a predefined option set mediated by (and within the boundaries of) the algorithmic management system.

Even drivers' deviance behaviors and the subsequent workarounds (e.g., drivers declining multiple consecutive rides and then requesting themselves as a rider from another pone) can be within the boundaries of the system since this leniency has been programmed, literally, into the algorithmic management system (Cameron, 2023). Taken together, this suggests that these tactics reinforce an illusion of choice for drivers while leaving organizational control in the on-demand economy in the hands of the on-demand organization itself.

37. *Gamification.* Another way organizations obfuscate control is by gamifying work, or applying elements of game playing (e.g., point scoring, competition with others) to work activities as a way to encourage workers to work longer hours. By gamifying work, the work itself becomes more fun and enjoyable while ensuring that workers' behaviors are aligned with the organization's interests—with the end result being that workers are controlled. Numerous scholars describe the gamification and psychological priming practices on ride-hailing and other on-demand apps (e.g., Irani, 2015; Rosenblat 2018; Ravenelle 2019; Schor, 2021; Manriquez, 2019). Embedded within the drivers' interface with the app are design features that encourage workers to work at specific times. A *New York Times* article, "How Uber Uses Psychological Tricks to Push Its Drivers' Buttons," describes how Uber uses behavioral science to influence when, where, and how long drivers work by incorporating videogame techniques, graphics, and non-cash incentives (such as encouraging drivers to stay on longer just as they are trying to log out with notices to beat yesterday's earnings) (Scheiber, 2017). (See also Rosenblat, 2018). On another closed labor platform, Instacart, shoppers report that the app design makes them feel like they are playing "Supermarket Sweep" each time they work which, in turn, can encourage individuals to work longer than intended as they are deeply absorbed in the game of work (Cameron, Chan, & Anteby, 2022). Gamification can encourage deep absorption into the work, leading workers to accept consecutive rides and to strive for hiring ratings at the expense of their own earnings or physical well-being.[5] In my research, I found drivers would skip meals and going to the bathroom in order to keep driving (Cameron, 2020, 2022, 2023).

---

[5] Some illustrative examples from depositions in this case bear that drivers prioritize their work at the expense of their own well-being. See Collins, pg. 152 ("One hour turned into almost three hours, but hey, Lyft is like a box of chocolates."); Ciccarelli, pg. 35 ("Sometimes I worked until 3:00 in the morning. The most rides I ever did in a

38. *Workplace Games.* Unlike gamification, which relies on rules designed by management to improve workers' affective experience and boost productivity (e.g., Deterding et al. 2011; Mollick & Rothbard, 2014), workplace games are a result of organic interactions between workers and touchpoints in their environment. Said differently, workplace games are the result of spontaneous interactions between co-workers, that reinforce workers' perceptions of status or skill in or at their work, and these games, which often align with organizational objectives, reinforce organizational control. From my study of ride-hailing drivers, I find that workers typically play one of two games—the relational game or the efficiency game (Cameron, 2022). In the *relational game*, workers craft positive customer service encounters, offering gifts and extra services, for example, in the pursuit of high customer ratings.[6] In the *efficiency game*, workers set boundaries with customers, minimizing any extra behavior, in the pursuit of maximizing money per time spent working.[7] These games can make work more meaningful and rewarding to individuals.

39. Elements of uncertainty in the game (e.g., fluctuating pay rates, unpredictable customers) can heighten workers' interest in these workplace games, making it more appealing for them and thus further increasing their work investment as they try to align their own behaviors to the goals of the organization. However, these workplace games and the worker's belief that they are "winning" the game, obfuscates how an organization can nonetheless exercise organizational control over its workers since the terms of "winning" are set by the organization. Indeed, the algorithmic management system and design elements of the user interface can reinforce drivers' games and encourage the playing of one game, that is more tightly coupled with organizational control, over another. For example, nudges encourage the

---

week was I did 200 rides in one week, and I was so tired I could barely drive home after that."); Bonham, pg. 141-142 ("No. I'm so busy, I don't take breaks.").

[6] Some illustrative examples from depositions in this case suggest that drivers play the relational game (knowingly or not). See Bonham, pg. 95-97, 132-134, 136-137 (returning items, providing a clean car, heated seats, taking riders where they wanted to go, and waiting longer for late rides because that is his business); Ciccarelli, pg. 25 (keeping care clean and talking with riders because that means a better experience for them); Kotsiopolous, pg. 265 (providing water to riders).

[7] For an example of a driver appearing to play the efficiency game, see Cabache, p. 68 (cancelling ride when he waits more than five minutes and passenger does not respond to his effort to contact them). Other drivers emphasized their focus on earning. Denny, pg. 101 (driver "striv[ing] to earn a thousand" a week); Gannon, pg. 9-10 (goal to earn $100 a night).

relational game (e.g., badges, rating systems) and discourages the efficiency game (e.g., incomplete ways to track time spent on app versus money earned) so that workers are more likely to behave in ways that are in alignment with the organization's objectives (Cameron, 2022).[8]

40. In summary, these three practices—constant and confined choice, gamification, and workplace games—can provide workers a sense of autonomy. However, this autonomy is largely illusory because it is artfully doled out by the algorithmic management system as a form of organizational control. In other words, while individuals may feel that they have choice surrounding their work activities, this choice is meted out by Uber's and Lyft's algorithmic management system as a way for workers to have limited choices in a system that was ultimately designed and controlled by Uber and Lyft.

V. How Uber and Lyft Use Algorithmic Management to Exercise Organizational Control Over Their Workers

A. The Use of General and Detailed Control by Uber and Lyft

41. Uber and Lyft deploy both general and detailed control through their algorithmic management systems. In the first section, I describe generally what is outlined in the community guidelines, deactivation policies, terms of service, and driver addendum which lay out the terms that drivers must meet to maintain their good standing with the ride-hailing company. Specifically, I discuss Uber and Lyft's upfront pricing, loyalty programs, and planned incentives. In the next section, I describe detailed control. Detailed control is more extensive in that it involves how the ride-hailing companies' algorithmic management systems shape drivers' everyday interactions.

[8] Illustrative examples from the driver depositions confirm that drivers change their behavior in response to incentives. Collins, pg. 161-162 (making "extra effort" to "complete 25 rides" to "earn an extra 65.00" incentive); Zorrok, pg. 34-35 (accepting more rides in response to Uber Quest incentives); Ciccarelli, pg. 74-75 (maximize time on the app by driving at busy times and achieving bonuses); Cabache, pg. 96-109 (responding to incentives because they afford him an opportunity to make more money); Hansen, pg. 53 (driving towards areas where high demand); Gannon, pg. 31-32 (describing wanting to maintain high star rating so that he is offered more rides).

B. General Control by Uber and Lyft

42. *Upfront Ride Pricing.* Historically, Uber and Lyft determined driver earnings via a rate card: Uber and Lyft charged riders a fare based on time and distance set by a rate card, drivers then earned an amount based on the percentage of the rider fare, and Uber and Lyft took a commission based on the entire fare charged to the rider (Rosenblat, 2018; Isaac, 2017). By 2018, however, both companies began decoupling driver earnings from rider fares by offering upfront pricing for rider fares, first in major metropolitan areas. The switch from rate cards to upfront pricing for rider fares introduces more opacity into the system in that riders were quoted a separate fare amount before the ride occurred and drivers were no longer explicitly paid based on the amount charged to the rider. (Rosenblat, 2018). Historically, drivers had a sense of how much they would earn for a ride, given the location, day, and time, and could project their earnings and get a sense of when the algorithm was acting unpredictably (i.e., not properly accounting for incentives a driver was entitled to; Cameron, 2022). However, in 2022 both companies introduced upfront pay for drivers. Under this structure, rather than set rates per mile and minute, driver earnings are algorithmically determined by Uber and Lyft, presented to the driver before the trip begins, and based on a combination of factors which are not fully disclosed to the drivers. For Uber and Lyft, upfront driver pay is designed to nudge workers to behave in a certain way, such as working at a certain time or location, that is in alignment with the organization's interest of having a sufficient pool of drivers available and ready to work to meet customer demand. This algorithmic opacity leaves drivers with even less insight into how key decisions are made about their work and more easily allows their actions to be even more easily shaped by Uber's and Lyft's algorithmic management system.

a. *Uber's Real-Time Dynamic Upfront Pricing.* In upfront pricing, Uber sets driver fares up-front based on marketplace dynamics that are specific to a particular place and a particular time (Dobbs, pg. 107-8, 117, 465-6). These driver fares are presented to the driver before they accept or decline the ride (Dobbs, pg. 1516-8; Uber-MA00238977; Uber-MA00238982). Driver fares are based on a base rate on estimated time (per-

minute rate), distance (per-mile rate) of a trip, distance to the rider pick-up location, real-time demand incentives and surges), tolls, surcharges, governmental service fees and Uber-derived service fees (Dobbs, pg. 628, 630, 640, 818-23, 1516-21; Uber-MA00247075-9, 7102-4). Surges (i.e., real-time algorithmically calculated demand incentives) are embedded into the fare calculation and can fluctuate due to market-based demand (Dobbs, pg. 828-31). Drivers do not have the ability to influence the driver fare amount presented to them (Dobbs, pg. 1521-2). And significantly, when drivers accept these rides, they are unable to see what the rider is being charged or the inputs that make-up the that amount (Dobbs, pg., 861-3).

b. Uber's data scientists and engineers build, maintain, and improve the algorithmic models that support Uber's dynamic pricing system and decide what features to implement and how those features might influence driver behavior (Dobbs, pg. 467, 865-6). And while Uber, per se, may not specifically set the surge amount or other specific details for each and every ride, Uber and its employees do retain unilateral control over ride pricing, write the software code, and determine the inputs and outputs of the real-time dynamic pricing system (Dobbs, pg. 641-2). Algorithms designed by Uber set the base rate based on variable situational factors (Dobbs, pg.1518-9). These base rates do not change based on a driver's seniority or rating, effectively meaning that drivers do not receive any premiums or wage adjustments for tenure or good performance (Dobbs, pg. 824-6). It is also possible that the inputs for base rate, rate per mile, and rate per minute could change from day to day (Dobbs, pg. 823-4).

c. Similarly, Uber's service fees are variable and are algorithmically based (Dobbs, pg. 1359-60). The service fee directly affects drivers' earnings (Dobbs, pg. 1349-50), but drivers are not presented with information about how the service fee is calculated and cannot negotiate the service fee amount (Dobbs, pg. 634-9, 859-60). And although much of Uber's revenue from ridesharing is derived by the service fees that riders and drivers pay to Uber on each ride (Dobbs pg.1356-8), Uber has no plans to surface the service fee to a driver prior to their acceptance of a ride (Dobbs, pg., 870-5). Because the service fees are hidden from the driver, drives are unaware of how much Uber

makes per ride and are unable to determine an accurate hourly wage or the actual value of the transportation service they are providing.

d. In summary, the upfront pricing that is part of Uber's algorithmic management system enables greater organizational control by Uber over drivers. By making pricing for driver pay opaque, Uber can more easily direct workers to take the rides that it desires them to take without drivers knowing how much Uber is earning from each ride. This is because while drivers can see some inputs into the fare calculation after the competition of the ride, they do not have insights into the rider price or variable fees, both of which are set by Uber. Further, drivers do not have this information available to them at the time they must decide whether to accept a ride request. Moreover, Uber optimizes the amount of driver pay for market efficiency which may or may not be the worker's best interest and does not adjust for workers' seniority or skill (Dobbs, pg. 635-7; 653-4).

[redacted]

[redacted]

[redacted]

[redacted]

43. *Planned Incentives and Loyalty Programs.* While upfront pricing allows Uber and Lyft to optimize for short-term demand/supply of riders and customers, the goals of Uber and Lyft's loyalty programs and planned incentives are two-fold: to encourage drivers to work in the short-term, at peak demand, and long-term retention. In other words, these loyalty programs and planned incentives aim to control drivers' behavior by keeping them working on the platform for a longer tenure. Programs such as Uber Pro and Lyft Rewards link workers' behaviors (e.g., ratings) to incentives that drivers value (e.g., priority access to ride, gas discounts). Unlike consumer loyalty programs, such as an airline rewards program, these programs affect workers' granular interactions with the work itself and workers' economic livelihood. For example, by keeping their customer rating above threshold, drivers may get additional information about their ride such as the destination address before accepting (historically) or access to priority rides at the airport (currently). To maintain this benefit, however, the drivers are required to keep their ratings high. These strategies reinforce the illusion that workers have autonomy, while the companies' algorithmic management systems are operating in ways that increase organizational control over the workers and consolidate power in the hands of the two companies.

44. A general finding across on-demand companies is that the majority of the work on these platforms, especially the most highly valued work (i.e., work at high-demand times), is done by a minority of drivers (Pareto's principle, 80/20 rule; Gray & Suri, 2019). Securing high-quality committed drivers is crucial to these companies' business models, as a disproportionate amount of their revenue is dependent on a minority number of workers. This principle applies to drivers at Uber and Lyft. Correspondingly, both companies have designed loyalty programs, Uber Pro and Lyft Rewards respectively, as well as individualized planned incentives, all aimed at encouraging driver commitment and retention

for their most highly valued drivers. In the following sections, I describe the loyalty programs and planned incentives designed by Uber and Lyft, deployed by their algorithmic management system and how they are used to influence and direct workers' behaviors.

a. *Uber's Loyalty Program, UberPro:* Offering great customer service, as indicated by higher customer ratings, and a longer-term tenure are signatures of drivers that contribute positively to Uber's bottom line (Dobbs, pg. 284-6).[9] Knowing that only a small percentage of their drivers are the highest value, loyalty programs such as Uber Pro are designed to retain the highest value drivers (Uber-MA248071-2; Uber MA0247931-8084). Churn is highest between drivers first and second year and this churn comes at a substantial cost to Uber, with incentives in one week in March 2018 alone reaching $20M (Uber 247956-961). The top 10% of cities in the United States and Canada produce over 80% of the weekly US and Canada trip total and drivers who qualify for loyalty programs complete 49% of these trips (Uber-MA247981). Moreover, the top 10% of cities in the US and Canada produce over 80% of the loyalty program trips. (Uber-MA247981). Along these same lines, Uber described loyal drivers as those who give great service, drive consistently, accept and complete rides, especially at peak times, choose Uber over other ways to earn, and are "willing to stay for the long haul" (Uber-MA248033-4).

b. Given the importance of this small segment of long-term drivers, Uber has invested considerable efforts in putting together a team to design programs and planned incentives that encourages drivers to remain committed to the Uber platform (Dobbs, pg. 240). The goals that are built-into loyalty programs are to keep drivers on the road longer and offer great, highly rated customer service (Dobbs, pg. 287). Uber describes the logic behind incentive programs and the importance of highly valued drivers as such: "If riders treat drivers well, those drivers are more likely to remain on the platform and if drivers provide good service to riders, those riders are more likely to continue to engage on the platform (Dobbs, pg. 286-7)." Similarly, emphasizing the

[9] Historically, Uber called the small percentage of drivers who completed a large percentage of drivers. High-value drivers are a minority of Uber's drivers--only one in 20 new drivers becomes a high value driver after a year driving (Uber-MA247957; Uber-MA248071-2; Uber-MA0247931-8084). These drivers are contributing positively to the bottom line of Uber (Dobbs pg. 242-8).

importance of customer service, Uber stated, "driver's service is likely one input into the rider's experience on the platform," whether they remain on Uber, switch to Lyft, or choose an entirely different method of transport (Dobbs, pg. 290). Underscoring the importance of the efforts is Uber's underlying business objective—the more drivers and customers participating in Uber's ridesharing network, the more effectively the network functions and the more profitable it becomes for Uber (Dobbs, pg. 286). Uber hopes that by participating in Uber Pro, of which all drivers are automatically enrolled in, drivers may modify their behavior (i.e., drive longer periods of time and have a longer turnover) and/or do things to improve their rating to qualify for certain tiers (Dobbs, pg. 282-8).

c. In Uber's Project Norway, Uber explored initial ideas and concepts for what later became the Uber Pro loyalty program (Dobbs, pg., 282). As part of Project Norway, Uber considered offering drivers perks such a tuition assistance, assistance for planning trips, and support in helping drivers launch their own businesses (Uber-MA248045-55). While starting a business is a professional goal reported by many drivers (Uber-MA248046), and Uber considered offering a perk to driver to help them achieve this goal (Uber-MA248050), Uber ultimately decided not to include this desired perk for drivers because if drivers successfully started their own businesses, they would no longer remain drivers (Uber-MA246010; Uber-MA248050). Thus, this incentive was not included into what later became the Uber Pro program.

d. Components of the Uber's Project Norway that were integrated into Uber Pro include identifying that some drivers provide more value to Uber than others (Dobbs, pg., 353-6; Dobbs exhibit 37), the linking of rewards to certain drivers (i.e., those with good ratings) (Dobbs, pg. 349, Dobbs exhibit 36 fn 3, pg. 244868), success metrics such as rider ratings and cancellation and acceptance rates (Dobbs, pg. 346; Dobbs exhibit 36), and testing awarding highly rates drivers with more rewards (Dobbs, pg. 385; Dobbs exhibit 41). Ultimately, a key goal of Uber Pro is to increase driver retention (Dobbs, pg. 282).

e. Uber wants drivers to see a progressive career within the Uber company with Uber Pro and Uber Pro Plus as one of these career steps (Uber-MA248048). However, driving for Uber is anything but a career. Careers are a specific sequence of jobs through which workers progress as they gain skills and experience (Bidwell & Briscoe, 2010). But there is no career progression driving for Uber. Indeed, the rides that drivers perform conform to the same standardized set of characteristics. Drivers never can take on different jobs, build skills that advance them beyond to their current position, or advance internally with the organization. Significantly, Uber pays longer-tenure drivers the same base rates as newcomers (Dobbs, pg. 635-7; 653-4). And, because paying drivers more will cost Uber more money (Dobbs, pg. 283) the loyalty programs are essentially trying to extract more labor from drivers without offering substantial benefits in return.

f. Uber goes on to describe how a potential loyalty program can "bind" drivers to Uber such that workers remain committed to Uber, driving at peak hours for years, and not drive for Uber's primary competitor, Lyft (Uber-MA248053-60). In one hypothetical scenario discussed in Uber's document production to the Attorney General, Uber Pro helps one driver (Roman) understand the value of starting his shift early so he can secure more trips during peak demands times (Uber-MA248053-60). And while another hypothetical driver (Sally) prefers Lyft and desires short and local trips, she continues to accept Uber's longer-trips because she knows top-tier status depends on a low cancellation rate. Uber explains this as follows: "Despite the annoyance [of a long-trip], her [Sally] pleasant attitude and safe driving result in another 5- star rating. She's always been careful to keep a high rating and now it impacts she status (Uber-MA248064)." After enrolling in an education program, Sally "continues to drive part-time in peak hours to maintain [] [her] status…She stops reading her Lyft emails altogether (Uber-MA248067; Uber-MA248061-69)." In both hypotheticals, Uber has so effectively designed its loyalty programs and planned incentives that it has exercised organizational control over workers by getting one driver to drive more during peak hours and secured another to an on-going commitment to Uber.

g. Priority goals of Uber Pro are to increase driver retention as well as improve drivers' customers service behavior (Dobbs, pg. 251-4, 282). Launched in Boston in February 2019, the Uber Pro loyalty program unlocks perks, such as gas discounts, tuition assistance, and roadside assistance based on driver's usage of the Uber platform and compliance with the rules set out by Uber (Dobbs, pg. 158; 295-6); (Uber-MA2962). When releasing Uber Pro, Uber clearly linked driver's long-term tenure to their financial success: 'We are planting seeds by rewarding our most valuable drivers that *we expect to pay off for our business*." (Dobbs, pg. 296; Uber-MA00245589; Dobbs exhibit 32) (emphasis mine). An Uber representative goes on to describe "The seed is Uber Pro" (Dobbs, pg. 296). Indeed, drivers state that one of their goals is to stay in good standing with Uber Pro (Zorrok, pg. 33-4). Another driver often checks if he is on the cusp on moving up to the Uber Pro Gold level, which provides more information about the riders, before he drives (Hyland, pg. 27-30).

h. Drivers are automatically enrolled in the Uber Pro program, earn points based on their driving activities (e.g., completing trips at peak times), and can reach different tiers levels based on their level of engagement which are linked to various awards, such as roadside assistance and priority phone support (Dobbs, pg. 161-2; Uber-MA00245925). To maintain their tiered status, drivers must follow the directives that Uber sets such as keeping their customers ratings at 4.75 and maintaining a cancellation rate under 4% (Dobbs, pg. 164; Uber-MA002959-65; Uber-MA00245924). As an example of how Uber Pro aims to influence drivers' behaviors towards customer, the 4.75 required to maintain tier status is above Uber's minimum rating to stay active on the platform. Drivers are also required to have a minimum acceptance rate of 75 percent over a rolling 30-day window (Dobbs, pg. 166; Uber-MA 2954-65). To be eligible to be considered to move to higher tiers, the driver can have no more than a 4 percent cancellation rate, but then if they wish to maintain their tier status there is a maximum cancellation rate of 10 percent (Dobbs, pg. 169). In another example of the long reach of Uber's organizational control, driver status

resets each qualifying period, so drivers must continuously exhibit desired behaviors to retain their status and rewards.[10]

i. Uber described Uber Pro as similar to an airline loyalty program (Dobbs, pg. 158); however, it is anything but. First, in Uber Pro there are terms and conditions—beyond the minimum remain in good standing with Uber—that must be met to achieve higher-level status. Second, one's tier directly affects drivers' interactions with the algorithmic management and, indirectly their income. In other words, drivers are not passive recipients of points – they must actively work for them and the quality of this work affects their economic livelihoods. Drivers at the top tiers of these loyalty programs add more value to the Uber platform than drivers in the lower tiers (Dobbs, pg. 359-61). At higher-tiered levels, drivers historically received more information about the ride (i.e., destination) before accepting (Uber-MA00245589-95; Uber-MA00002963). In the current version of Uber Pro, drivers at the highest tiers receive additional benefits from the algorithmic management system, such as having priority positioning in the airport queuing system or the ability to request trips in a certain direction (Uber-MA2963). Each of these are examples of constant and confined choice (see pg. 18). By following the directives of the algorithmic management systems, i.e., by actively being subject to even more organizational control, drivers can get a small amount of autonomy, in the form of additional information or the ability to have more choices, within the confines of the algorithmic management system. This information and rewards came with a cost, in that drivers must continue to keep their cancellation rates low and their customers ratings high to receive these benefits.

j. Moreover, many of the perks provided by Uber Pro directly benefit drivers by helping them ensure their cars are running smoothly (e.g., roadside assistance, priority phone supports discounts on car maintenance), something that, in turn, benefits Uber (Uber-

[10] Recent documentation stated the current qualification period is three months: https://www.uber.com/au/en/drive/uber-pro/#:~:text=With%20Uber%20Pro%2C%20there%20are,earn%20points%20by%20completing%20trips.

MA2962). Taken together, the Uber Pro program is an example of the self-reinforcing and cyclical nature of organizational control at Uber in that while drivers may feel like they are receiving perks from Uber these perks are yet another way that Uber is influencing driver behavior.

[redacted]

[redacted]

[redacted]

[redacted]

45. *Planned Incentives.* Planned incentives are another feature of Uber and Lyft's algorithmic management system that enables organizational control over drivers. The goal of planned incentives is to induce drivers to work for longer hours, often at the times preferred by Uber and Lyft, and to continue working for Uber and Lyft over the long-term.

a. *Uber's Planned Incentives.* Uber uses planned incentives to influence and shape driver behavior. Examples of planned incentives include DxGy (Do X and Get Y),

Quest, and offering rewards if drivers work at peak hours or complete a certain number of consecutive rides (Dobbs, pg. 172, 307-12, 677-9, 1377; Uber-MA88962; Uber-MA50526, 71237, 71413). These incentives increase the long-term loyalty of drivers and address driver churn (i.e., an undersupply of drivers, which would undermine Uber's business objectives) (Dobbs, pg. 255-6; 403-6). In other words, one of the purposes of planned incentives is to increase the long-term loyalty or tenure of drivers (Dobbs, pg. 225-6). Uber notes that it has issues with the retention of drivers, with only three out of twenty drivers still active at the end of the year and only one of twenty retained being high quality (Uber-MA245965-246025; see especially 245966; 245987, 245995-6, 246010). Indeed, Uber considered offering incentives that paid for part of college tuition or gave funds towards a trip; however, it was wary of offering incentives that could encourage drivers' entrepreneurship or small business development because this might lead drivers to stop driving (Uber-MA246010).

b. Having drivers remain active on the platform, giving high-quality rides, is important for Uber's business model. Uber's Rule 30(b)(6) designee, Chad Dobbs, (pg. 1381) described the relationship between planned incentives and Uber's business model as: "The more drivers you have and more riders you have, the effective[ly] the marketplace works. And the more effective the marketplace works, the less you have the fill the gaps in the marketplace with [planned] incentives." Uber's Project Norway, a pre-cursor to Uber's Uber Pro program, was designed to develop new driver incentives and to address the issues of worker retention. A description of Project Norway states, "We offer rewards that are non-monetary benefits, experiences, and recognition as well as today's cash earnings and incentives. We seek to motivate longer-term commitment, not just short-term ride targets (Dobbs, pg. 282; Uber-MA245965; Uber-MA245965-246025)." Boston is identified a priority market for testing new planned incentives such as Project Norway (Uber-MA245701).

c. Planned incentives can be helpful in making sure that drivers are on the road in high demand times (Dobbs, pg. 355-60). Drivers report these incentives keep them on the

road longer (Zorrok, pg. 37), influence them to take shorter trips (Zorrok, pg. 35), and influence their overall behavior while driving (Hyland, pg. 63, 72). Emotional levels can be pulled on to influence workers, Uber notes that some drivers can be motivated to meet these incentives because they were proud of their status and wanted to unlock a certain perk (Dobbs, pg. 227-8). While Uber states features like surge pricing and Quests simply facilitate marketplace operations and are not controlling anyone (Dobbs, pg. 1195), these features are classic examples of organizational control because they attempt to align workers' efforts with Uber's organizational objectives.

d. In an example of gamification (pg. 19), Uber has designed iOS widgets that present the planned Quest incentive as a game (Uber-MA88594). "The Quest widget reduces the number of interactions it takes to view valuable information when out of the app and allows drivers to explicitly goal set and track their progress. The notion of quest competition adds an element of *gamification* creating immediate actionability and ultimately an incentive to drive" (Uber-MA0088594). Immediately following the description of Quest, Uber has included a quote from a driver describing how this gamification makes work more fun and influences them to work longer. More generally, Uber send drivers frequent updates on their monthly trips, times they were tipped, and loyalty status giving workers a sense of their ranking in their systems (Uber-MA00070735).

e. In summary, the planned incentives that are designed and maintained by Uber's algorithmic management system enable Uber to have greater organizational control over drivers. These incentives are individually tailored to drivers, enticing them to work at the periods of time and places that Uber desires. More broadly, the incentives are designed in such a way to increase drivers' job satisfaction and earnings experience such that they remain working for Uber.

[redacted]

[redacted]

h. In summary, the planned incentives that are designed and maintained by Lyft's algorithmic management system enable Lyft to have greater organizational control over drivers. These incentives are individually tailored to drivers, enticing them to work at the periods of time and places that Lyft desires. More broadly, the incentives are designed in such a way to increase drivers' job satisfaction and earnings experience such that they remain working for Lyft.

46. *Uber and Lyft's Algorithmically Mediated Customer Ratings System*. Uber and Lyft's algorithmically mediated customer rating systems allow the companies to launder their

organizational control through customers. Customers are prompted to rate drivers after every ride and drivers who receive poorer ratings face sanctions. Moreover, drivers have limited means at their disposal to refute ratings they deem were unfairly given by customers. To ensure consistent service encounters, Uber and Lyft curate customer-worker interactions through prescribing "service rules" about what specific emotions to display and behaviors to engage in that are then evaluated by the customer. Ensuring drivers deliver good customer service is important for the companies' business models because satisfied customers will continue using the service. To ensure that drivers behave accordingly, the customer ratings systems evaluate driver's behaviors, with drivers with poor ratings facing sanctions and possible deactivation from the platform.

a. *Uber's Customer Ratings and Related Warnings, Suspensions, and Deactivations.* In Boston, Uber deactivates drivers with a rating lower than 4.5 and issues warnings for drivers with warnings below 4.65 (Dobbs, pg. 968; Uber-MA389887-92). However, while drivers are held accountable to keeping a overall customer rating they are unaware of the specific rating they receive from each customer (Uber-MA1634).
b. High ratings are important to drivers (Zorrok, pg. 32; Cambridge, pg. 22-3; Gannon, pg. 31-2; Hyland, pg. 43), especially because it effects their levels and standing with the Uber Pro loyalty program (Zorrok, pg. 32-4; Hyland, pg. 43). Uber also sent video tips to drivers about how to provide high quality service (Gannon, pg. 32-3). Drivers watched these videos (Gannon, pg. 32-3; Hyland, pg. 47-9, 66-7). Some drivers even purchase water, chargers, and candy from their own funds in order to offer a better customer service experience to riders (Hyland, pg. 62; Cambridge, pg., 45-8; Zorrok, pg. 54).

c. As described earlier (pg. 20), caring about customer ratings, and providing amenities are elements of the relational game in which drivers spend considerable efforts to satisfy customers in order to "win" the game. Describing the emotional high he got after providing amenities to riders, one driver said: "It was a nice thing to, you know, a 90-degree day, somebody's walking through Boston and they want a ride home, they hop in the car, they're sweating and I say, hey, do you want a bottle of water, and they think I'm the greatest thing since sliced bread, and everybody wanted to

charge their phone so I just had the chargers ready to go" (Cambridge, pg. 45). Describing why customers' ratings was important to him, this driver said: "Because I'm a perfectionist and I like to do a good job" (Cambridge, pg. 22-3). Similarly, when another driver was asked why he cared about customer ratings, this driver said: "Quality. I like to do a good job no matter what I'm doing." (Gannon, pg. 31-2). A third driver mentioned how much customers loved his service and thanked him (Zorrok, pg. 45). Drivers become so vested in the game they do not decline rides. One driver declined only three rides during his entire tenure at Uber (Gannon, pg. 31), in part, because he believed (mistakenly) this might hurt his rating (Gannon, pg. 31-3). Altogether, the emotional highs of interacting with customers can keep drivers working and aligning their behaviors to Uber's algorithmically mediated customer ratings system.

d. As described earlier (pg. 38), Uber's algorithmically mediated customer ratings are a way for Uber to launder control through customers. In laundering control through customer ratings, Uber claims that they are not exercising organizational control (because the riders are doing the rating), when in actuality it is Uber that has designed the customer rating system, and the thresholds drivers must keep to maintain access. This is borne out in the Rule 30(b)(6) testimony of Uber's designee, Chad Dobbs. On the one hand he eagerly disclaimed Uber's role in the rating's process (see Dobbs, pg. 970-971) ("(Q): Is it fair to say that a driver who was deactivated for failing to meet the minimum star rating is being deactivated because they did not meet Uber's standards for service to riders in the platform in that region? (A): No, I don't think so. As we talked about, the ratings come from riders. Uber doesn't play any part in giving ratings or anything like that. And so it's ultimately what the standards and expectations are of the rider that dictates the ratings the driver gets and therefore whether they're able to continue to operate on the platform."), but then readily admitted that Uber sets the underlying rating threshold for drivers (Dobbs, pg. 971). Thus, while Uber does not give the actual ratings, it created the system for doing so, prompts riders to give those ratings, and takes action against drivers based on the ratings that riders input.

e. If deactivated, Uber requires drivers to pay for and complete an approved quality improvement class to be considered for re-activation (Uber-MA0000585, pg. 589; Uber-MA003898877; Uber-MA001634, Uber-MA00389886; Dobbs, pg. 38-9; exhibit 101); however, all drivers may not be offered the opportunity to take this training (Uber-MA0001621, pg. 1634). Drivers may also take the class voluntarily to learn how to achieve a five-star rating (Uber-MA003898877). The presence of such classes provides further data to support the claim that Uber has service rules for how drivers are to behave towards customers; failure to follow these rules results in negative consequences for drivers (e.g., being unable to regain access to the app). Regaining access after a deactivation is difficult. The Independent Drivers' Guild in New York City, which represents over 10,000 ride-hailing drivers, estimates that less than 10% of arbitrated deactivation appeals result in reactivation on the app, pointing to the irrevocability of Uber's decisions over drivers' fate on the platform (Price, 2018).

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

m. *Customer Abuse in Ratings Systems*. Using algorithmically mediated customer ratings to evaluate customers is particularly problematic because ride-hailing drivers are at high-risk of customer abuse. Many drivers reported being temporarily or permanently suspended from the app after complaints from a customer who was upset because they were not given preferential treatment (e.g., food stops) or because drivers enforced a safety regulation (e.g., car seats for children) (Maffie, 2022; Cameron, 2020). One driver I interviewed was temporarily deactivated because his car smelled like marijuana even though the driver explained this was because he had recently transported a rider from a dispensary (Cameron, 2018). Moreover, customers may fabricate complaints assuming that the on-demand company is likely to take their side and offer them a refund (a situation that has only increased after the height of the COVID-19 pandemic)[12] (Ravenelle, 2020). However, there is no systematic way that

[12] Drivers have reported being deactivated for unknown reasons or based on unfounded accusations by riders, often without any advance notice. Dep. of John Bonham at 52; Dep. of Alexander Baah at 21; Dep. of Raya Denny at 113-116; Dep. of Hristos Kotsiopoulos at 154-156.

a ride-hailing company can know what caused a customer to give a poor rating since customers are not required to provide justification for their ratings (Cameron & Rahman, 2022). When drivers try to fight customer allegations, such as through purchasing dash cams that record their interactions with customers, this evidence can be ignored.

n. Uber drivers note they are sometimes victims of false complaints and have to spend time not working to defend themselves (Zorrok, pg. 49-50).

[redacted]

47. *Reactivation.* One of the ways that Uber and Lyft exercise control over workers is by making it extremely difficult for drivers to get reactivated if they are deactivated. Because of the finality of deactivation, this may make workers more wary about not following Uber or Lyft's rules and nudges.

a. If deactivated, Uber requires drivers to pay for and complete an approved quality improvement class to be considered for re-activation (Uber-MA0000585, pg. 589; Uber-MA003898877; Uber-MA001634, Uber-MA00389886; Dobbs, Rough Transcript 10/6/23, pg. 38-9; exhibit 101); however, all drivers may not be offered the opportunity to take this training (Uber-MA0001621, pg. 1634). Drivers may also take the class voluntarily to learn how to achieve a five-star rating (Uber-MA003898877). The presence of such classes provides further data to support the claim that Uber has service rules for how drivers are to behave towards customers; failure to follow these

rules results in negative consequences for drivers (e.g., being unable to regain access to the app). Regaining access after a deactivation is difficult. The Independent Drivers' Guild in New York City, which represents over 10,000 ride-hailing drivers, estimates that less than 10% of arbitrated deactivation appeals result in reactivation on the app, pointing to the irrevocability of Uber's decisions over drivers' fate on the platform (Price, 2018).

[redacted]

E. Detailed Control at Ride-Hailing Companies

48. Detailed control refers to organizational control over the execution of the work itself, including the pace of work, allocation of tasks, performance evaluations, and discipline. Before explaining how Uber and Lyft deploy detailed control, I will describe the mechanics of a driver completing a ride (Rosenblat, 2018; Cameron, 2020; 2023), which, at this level of generality, is virtually identical for both companies. Drivers begin to work by first choosing a location to open their app and swiping right to go "on-line." A complete ride consists of 1) the app matching the driver and rider; 2) the driver accepting the ride; 3) the driver getting the rider's location, driving to the rider's location, and waiting for the rider to enter the vehicle; 4) the driver swiping "start ride" on the app and entering the destination on the app; 5) the driver and rider interacting; 6) the driver dropping the rider off; and 7) the driver swiping "end ride" and both the driver and the rider being prompted to rate the other (however, only drivers are required to rate the ride before being matched again). Rides may end prematurely, such as when a rider fails to show up or the app malfunctions. If not matched to another ride before a trip is complete, then at the end of a ride drivers may stay "on-line" and wait to be matched again or go "off-line" and stop working.

49. Algorithmic management systems exercise detailed control over workers by 1) matching them to riders; 2) determining the price of the ride; 3) guiding the pace of their work (e.g., determining when the next ride is added to the queue for shared rides); and 4) evaluating performance through computing an overall average of customer ratings (Cameron, 2023). In a typical period of driving a driver may only complete a dozen rides but will have more than a hundred unique interactions with the algorithm (Cameron, 2020; 2023). Each of these unique human-algorithm interactions is a site of constrained choice in that workers have limited choices available to them to remain in good standing with the on-demand organization (see pg. 18; Cameron, 2020; 2023). Thus, while drivers do have some schedule flexibility in determining the times and location in which they begin working, once they begin working their choices are constant yet constrained in that they must follow the algorithm's directives and nudges in order to remain active on the app and earn money.

50. *Uber and Lyft's Matching Algorithm.* Uber and Lyft rely on algorithmic blind matching in which the algorithm matches drivers to riders on a series of factors that are not visible to the rider or driver (but are known to the company itself). As a result, workers state they do not know if they are receiving the "best" ride or perhaps if they are being punished by the algorithmic management system for some reason outside of their personal control (Cameron, 2022). Historically, drivers did not have any control over what rides they are assigned, where they are going, and the duration of their trip. Recent changes have given drivers more discretion in matching, but as explained below the parameters of this choice are still governed by the companies' matching algorithms. Below, I describe Uber and Lyft's matching algorithms.

    a. *Uber's Matching Algorithm.* Uber created the matching algorithm that links drivers and riders and makes improvement to the algorithm as needed (Dobbs, pg. 728-31). Inputs into the matching algorithm include rider pickup location and destination, the product riders have selected, driver location, and the drivers in the area (Dobbs, pg. 740). Uber's matching algorithm optimizes for the best decision for the network as a whole, a process that can include forward dispatching or offering rides to drivers before they have completed an in-progress trip (Dobbs, pg. 741). It does this through

a process it refers to as "batch matching." In batch matching, instead of matching each individual ride request with the closest driver for that rider, the algorithm will consider a batch of ride requests for a given geographic area, and surfaces ride requests to nearby drivers in a way that "ultimately make[s] the best decisions for the network on the whole." (Dobbs, pg. 739-41). At times, the matching algorithm may elect to send a ride request to only one driver, or multiple drivers—how and when it does so is dependent on "what leads to a healthier marketplace." (Dobbs, pg. 744-46). In regular rides, drivers have fifteen seconds to determine they will accept a ride (Dobbs, pg. 1275). If drivers take a break from driving, Uber send messages to encourage drivers to sign back on (Uber-MA00005343, 50526; 52577; 65616).

b. In Trip Radar, drivers may be provided with multiple fares to choose between, with Uber providing drivers with some information about the ride up-front such as an estimated fare, the approximate length of the ride, and/or destination (Capoot, 2022; Dobbs, pg. 1262-5; Uber-MA278977). Drivers cannot negotiate these fares (Dobbs, pg. 851-3; Zorrok, pg., 23; Gannon, pg. 22-3; Hyland pg., 36-7). Uber's app makes the list of rides offered to the drivers based on parameters that the drivers input (Dobbs, pg. 115-6; 1262-9; Uber-MA00238977). Still Uber has the ultimate discretion regarding which trips are surfaced on Trip Radar (Dobbs, pg. 178, 1266). The time a driver has to accept a request depends upon the time it takes other drivers to see the same trip request and accept (Dobbs, pg. 1274-8). As previously described (pg. 18), Trip Radar is an example of constant and confined choices. Ultimately, while deciding between one or more fares does offer workers some choice these choices are from a limited option set that is defined and controlled by Uber.

c. When Uber drivers are presented a match they have only fifteen seconds to make a choice about whether to accept the ride (Dobbs, pg. 1275; Hyland, pg. 27; Zorrok, pg. 38-9). When asked about how he can make a decision under such time-constraints, a driver said: "Like I said, you do this so many times every day, six days a week" (Zorrok, pg. 40). As already described (pg. 18), this example highlights the constant, if constrained, choices that drives have in conducting their work.

[redacted]

[redacted]

[redacted]

51. *Uber and Lyft's Experimentation on Drivers.* Uber and Lyft use experimentation to drive strategic decision-making, a unique strategic tool used by on-demand organizations (Rahman et al., 2023). Through experimentation, the companies can test out new features and their effect on the companies' business objectives. While drivers generally agree to be "guinea pigs" when agreeing to the terms of services they are unaware of the specific terms of each experiment and how this data is being used by Uber and Lyft to better "capture" drivers' attention and to increase the organizational control exercised by their algorithmic management systems.

a. *Uber's Experiments on Drivers.* Uber has conducted experiments on drivers and riders including: UberPro (Dobbs, pg., 1010; Uber-MA00245944), widget installation (Uber-MA-88595), TripRadar (Zorrok, pg. 24), push notification (Dobbs, pg. 577-9), surges (Dobbs, pg. 660-3; Uber-MA00086506), pre-churn guarantees (Dobbs, pg., 402; Uber-MA00085193. During the same time period, for example, some Uber drivers in Boston received upfront pricing and trip Radar (Zorrok, pg. 24, 37-9;

Cambridge, pg. 30-1) while others did not and had never heard of the service (Gannon, pg. 26-8; Hyland, pg. 41-2). Results from these experiments are integrated in new versions of the Uber app. For example, given that Uber Pro was launched to segments of drivers in its initial target cities in 2018, Uber was able to conduct experiments to see how drivers responded to Uber Pro and test if their hypothesis around influencing drivers' behavior was accurate (Dobbs, pg. 295-6; Uber-00245944).

b. In part because of this rapid experimentation, drivers do not understand the intricacies of Uber's algorithmic management system. Some drivers note that acceptance and/or cancellation rates are important to them (Zorrok, pg. 30-1; Cambridge, pg., 33-4; Gannon, pg. 31,35), others do not find these rates as important (Hyland, pg. 32), and others do not fully understand how the algorithmic management system works—one driver believes that their acceptance rating is tied to their customer ratings and declining rides will hurt their chances of receiving future rides (Gannon, pg. 31-6). In general, Uber drivers are unaware if they are part of experiments or how the algorithmic management system makes decisions in general. This opacity and information asymmetry allow Uber's algorithmic management system to run so efficiently, in that workers do not actually understand how the decisions undergirding their work are made and how Uber is exercising organizational control.

[redacted]

[redacted]

52. *Geo-tracking and Other Monitoring of Drivers' Activities.* Another way that Uber and Lyft's algorithmic management system controls workers is through monitoring their location while

---

[redacted]

driving. Monitoring and organizational control are closely linked because through location monitoring, Uber and Lyft can track drivers' location and render penalties for (supposed) non-compliance to rules.

a. *Uber's Geo-tracking and Other Driver Monitoring.* Uber monitors drivers' behaviors through GPS tracking on every ride (Uber-MA0002915; Dobbs, pg. 83-4; Hyland, pg. 37). Monitoring and organizational control are closely linked because Uber uses driver location data to detect unsafe driving behavior or fraudulent activity (e.g., taking what Uber deems a less direct route, which can then be grounds for deactivation) (Dobbs, pg. 774-8; Dobbs, pg. 697-8 ;Uber-MA002915; Uber-MA00355085 pg. 4; Uber-MA0002800 pg. 4). GPS tracking automatically tracks if drivers go to the correct pick-up location and drivers are required to wait five minutes at the customer's pick-up location for them to arrive (Zorrok, pg. 42). As a part of their safety features, Uber informs riders that all its rides are tracked by GPS, and it can detect if a trip goes unusually off-course or if a possible crash has occurred. (UBER-MA0002800, pg. 4). Uber also uses driver GPS data to detect unsafe driving behavior, like exceeding the speed limit, and to inform them of safer driving practices. (Dobbs, pg. 774-78; UBER-MA0002915, pg. 10-11). In addition to geo-tracking, Uber also has the ability to collect information about other applications on drivers' phones (e.g., driver's activity on competitor platforms such as Lyft), either through surveys or other methods (Uber-MA00247931-4; 7941; 7963; 7972;7974; 7978; 7985; 8072; Uber-MA00245589-97; Uber-MA246714-6).[14]

[redacted]

[14] Two programs provide example of a historical pattern of Uber's organizational control: 'Hell' and "Greyball." The Hell program enabled algorithms to track drivers' location and smartphone activity even when they were not logged onto the Uber app allowing it to potentially penalize or incentive workers who drove for competitors (Kharpal, 2017; Isaac, 2019). Within the "Hell" program the "Heaven" view allowed Uber employees to track ordinary citizens, such as potential employees or journalists who criticized the company. In the "Greyball" program, government officials suspected of questioning or challenging Uber's activities were denied services from the app—the app showed them that no cars were available (even though there were cars in the area) the app showed them that no cars were available (even though there were cars in the area) or assigned phantom cars that never arrived (Wong, 2017; Isaac, 2019). To the best of the author's knowledge, Greyball stopped being used in the U.S. in 2016, but is still used in other countries.

[redacted]

VI. Narratives that Ride-Hailing and On-Demand Organizations Use to Influence Workers

A. Cultural Narratives that Ride-Hailing and Other On-Demand Organizations Drawn Upon to Influence Workers

53. In addition to algorithmic management, on-demand organizations draw on socio-cultural narratives on entrepreneurship and hustle culture, glamorizing on-demand work. Called possessive individualism, in this narrative individuals' own positions and actions are

emphasized; this emphasis attenuates individuals' relationships to one another, the state, and the common good (Macpherson, 1962). Said differently, when individuals understand themselves as masters of their own fate, they are less critical of other forces, such as organizations and the state, that may play a role in their circumstances (Burawoy, 1985).

54. When on-demand organizations encourage workers to think of themselves and other workers as entrepreneurs, possessive individualism is heightened. Entrepreneurship or small business ownership is a deeply lauded American value (Streeter, 2015). Indeed, many drivers aspire to be entrepreneurs (Uber-MA00247931, 248050, 245965). And on-demand companies draw on the "romance of entrepreneurism" (Ravenelle 2017: 281) to incentive workers (cf., Levy, 2023 for a similar example of the shift of truck drivers from employees to entrepreneurial owner-operators). In ride-hailing workers are explicitly told by on-demand organizations that they are *not* organizational members, and instead are called "entrepreneurs," "co-creators," "consumers," "service providers" or "partners" (Ravenelle, 2019). The term "Uberpreneur" has appeared in *Forbes* business magazine (Youshaei, 2015). Uber has a series of video vignettes on "Uber Entrepreneurs," who are both entrepreneurial by driving and also using their driving income to support other entrepreneurial "passions."[15] And advertisements from these company reinforce these narratives, telling workers to "Ditch the 9 – 5" and "Be Your Own Boss", implying that workers are entrepreneurs and the crafters of their own destinies. Another outcome of workers seeing themselves as entrepreneurs is that it limits their ability to coordinate with one another, for any type of collective action, because they see themselves as competitors trying to outdo one another (Chai & Scully, 2020).

55. The moralization, normalization, and heroization of long hours, being available, and 'doing' is a part of the image of being an "ideal worker" (Cameron, Thomason & Conzon, 2021; Goffman, 1963; Reid, 2015). In popular media, this is often described as "hustle culture", in that there is more to strive for: more money to make, a bigger title or promotion to secure and a higher ceiling to smash through (Hill, 2020). Referencing hustle culture and on-demand

[15] Examples of "Uberprenreurs" videos: https://www.youtube.com/watch?v=Tls9oV4WmFI
https://www.youtube.com/watch?v=udQNv6DzGxI
https://www.youtube.com/watch?v=Eiq68uYHGOA
https://www.youtube.com/watch?v=hOFFCiJR2Us

work, a *New Yorker* article titled, "The Gig Economy Celebrates Working Yourself to Death," describes the promotional materials directed to the workers of Fiverr, a freelance labor platform that glorifies a culture of overwork and sleep deprivation: "One ad, prominently displayed on some New York City subway cars, features a woman staring at the camera with a look of blank determination. 'You eat a coffee for lunch,' the ad proclaims. 'You follow through on your follow through. Sleep deprivation is your drug of choice. You might be a doer.' In one video, a peppy female voice-over urges 'doers' to 'always be available,' to think about beating 'the trust-fund kids,' and to pitch themselves to everyone they see, including their dentist" (Tolentino, 2017).

56. Similar morally laden messaging was targeted at potential on-demand workers during the height of the COVID-19 pandemic to encourage them to sign up on the app and work long hours.[16] Instacart advertisements, for example, called individuals essential workers and went as far to describe them as "heroes" because of their ability to get the right type of cheese for customers (Cameron, Chan, and Anteby, 2022). And on the labor platform TaskRabbit, workers even hid their risk preferences (e.g., hiding the fact they were wearing masks) to be eligible for more jobs on the platform and maintain their high customer ratings (Cameron, Thomason & Conzon, 2021).

57. The schedule flexibility afforded by on-demand work can help support the idea that drivers may see themselves are entrepreneurs, hustling on their own terms (c.f., Occhiuto, 2017 for a similar argument about how schedule flexibility allowed taxi drivers to see themselves as "family men"). Yet many scholars have argued because many workers are financially dependent on the work, their schedules are determined by when there is peak demand and not truly discretionary (e.g., Ravenelle, 2018; Rosenblat, 2018; Shevruck et al., 2018). A quote from James Parrott, the director of economic and fiscal policy at the Center for NYC Affairs

[16] See ride-hailing videos: (1) Thank You Kristin: https://www.youtube.com/watch?v=1m2KPtDYQ0s; (2) Thank You to All Drivers & Delivery People: https://www.youtube.com/watch?v=wOMrfZRrRq4. See also a more general example of moralization language calling Uber driver "everyday giants" (Uber-MA31390).

at the New School, best encapsulates this phenomenon: "It's a fiction that the workers really have flexibility. Sure, they can go on at 2 a.m. in the morning, but they're not going to get paid so why would they do that?" (Hu, 2022). Following this logic, workers' schedule flexibility is flexibility in name only as individuals must work specific hours in order to earn a living.[17]

58. Cultural narratives are sticky, providing insights into why individuals behave in ways that are not always in alignment with their own interests. For example, cultural narratives around autonomy and self-reliance explain why those in agricultural-based occupations (e.g., farming) support and vote for policies that undermine environmental protections for the very land that they depend on for the economic livelihoods (Hoschild, 2019). Narratives around entrepreneurship and hustle culture obscure exploitative elements of on-demand work because workers are able to imagine themselves as having more autonomy and choice than they may actually have. Noting the distinct pleasure that comes from embracing these seemingly empowering narratives, McMillam-Cottom (2020: 446) writes, "Knowing the extractive terms of their labor does not diminish [workers] enjoyment of the job. Platform capitalism owes much of its dominance to how good it feels to be captured by the platform." In summary, broader cultural narratives that are supported and endorsed by on-demand organizations are one of the reasons that make this work so sticky, and it is less likely that workers are able to realize and vocalize the extent to which their actions fall under organizational control and are being guided and controlled by algorithmic management systems.

Lindsey D. Cameron

Lindsey D. Cameron, Ph.D.
12 October 2023
Princeton, New Jersey

[17] For one illustrative example of a driver doing as much, see Ciccarelli, pg. 74-75 (maximizes time on the app by driving at busy times, achieving bonuses, and driving in areas where there is demand for rides).

References

Alkhatib, A., & Bernstein, M. (2019). Street-Level Algorithms: A Theory at the Gaps Between Policy and Decisions. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–13). Association for Computing Machinery.

Ajunwa, I. (2023). *The Quantified Worker: Law and Technology in the Modern Workplace*. Cambridge University Press.

Bansal, P. & Corley, T. (2011). The Coming of Age for Qualitative Research: Embracing the Diversity of Qualitative Methods. *Academy of Management Journal, 54*(2), 233-37.

Bartunek, J.M., Rynes, S. L., & Ireland, R. D. (2006). What Makes Management Research Interesting, and Why Does It Matter? *The Academy of Management Journal, 49*(1), 9-15.

Batt, R. (1999). Work Organization, Technology, and Performance in Customer Service and Sales. *ILR Review*, *52*(4), 539-564.

Bechky, B. A. & O'Mahoney, S. (2015). *Leveraging Comparative Field Data for Theory Generation*. Routledge.

Borkholder, Joy, Mariah Montgomery, Miya Saika Chen, and Rebecca Smith. (2018). *Uber State Interference: How Transportation Network Companies Buy, Bully, and Bamboozle Their Way to Deregulation*. National Employment Law Association.

Burawoy, M. (1974). *Manufacturing Consent: Changes in the Labor Process under Monopoly Capitalism*. University of Chicago Press.

Burawoy, M. (1985). The Politics of Production: Factory Regimes Under Capitalism and Socialism. Verso Books.

Burawoy, M. (2017). On Desmond: The limits of spontaneous sociology. *Theory and Society*, *46*, 261-284.

Burrell, J. (2016). How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. *Big Data & Society*, *3*(1).

Cameron, L., (2018). *The Feminization of Gig Work.* Harvard Business School Gender and Race Conference. May 2018.

Cameron, L. (2020). *The Rise of Algorithmic Work: Implications for Managerial Control and Worker Autonomy.* [Doctoral Dissertation.] Ross School of Business, University of Michigan.

Cameron, L. (2021). (Relative) Freedom in Algorithms: How Digital Platforms Repurpose Workplace Consent. In Sonia Taneja (Ed.), *Proceedings of the Eighty-first Annual Meeting of the Academy of Management.* Online ISSN: 2151-6561.

Cameron L. (2022). Making out While Driving: The Relational and Efficiency Game in the Gig Economy. *Organization Science.*

Cameron, L., Anteby, M., & Chan. (2022). Heroes from Above and But Not (always) from Within: Gig Workers Responses to the Sudden Moralization of their Work. *Organizational and Human Decision processes.*

Cameron, L., Lamers, L., Leicht-Deobald, U., Lutz, C., Meijerink, J., & Möhlmann, M. (2023). Algorithmic management: Its implications for information systems research. *Communications of the Association for Information Systems*, *52*(1), 23.

Cameron, L., & Meuris, J. (2022). The Perils of Paycheck Dispersion: When Fluctuation in Compensation Undermine Retention. n Sonia Taneja (Ed.), *Proceedings of the Eighty-secondAnnual Meeting of the Academy of Management.* Online ISSN: 2151-6561.

Cameron L, Rahman, H. (2022). Expanding the Locus of Resistance: Understanding the CoConstitution of Control and Resistance in the Gig Economy. *Organization Science.*

Cameron, L., Rosenblat, A. (2020). Gig Work Used to Be a Recession-Proof Safety Net. Not Anymore. *Fast Company*. https://www.fastcompany.com/90537938/gig-work-used-to-be-a-recession-proof-safety-net-not-anymore

Cameron, L., Thomason, B., & Conzon, V. (2021). Risky Business: Gig Workers and the Navigation of Ideal Worker Expectations During the COVID-19 Pandemic. *Journal of Applied Psychology.*

Capoot, J. (2022). Uber unveils new features, including one that lets drivers choose the trips they want. CNBC News. Accessed on 3 Sept 2023 at https://www.cnbc.com/2022/07/29/uber-will-let-drivers-choose-the-trips-they-want-to-take.html

Cardinal, L. B., Sitkin, S. B., & Long, C. P. (2004). Balancing and Rebalancing in the Creation and Evolution of Organizational Control. *Organization Science*, *15*(4), 411–431.

Chai, S., & Scully, M. A. (2019). It's about distributing rather than sharing: Using labor process theory to probe the "sharing" economy. *Journal of Business Ethics*, *159*, 943-960.

Charmaz, K. (1996). *Constructing Grounded Theory. A Practical Guide Through Qualitative Analysis.* Sage Publications.

Clemes, S. A., O'Connell, S. E., & Edwardson, C. L. (2014). Office Workers' Objectively Measured Sedentary Behavior and Physical Activity during and outside Working Hours. *Journal of Occupational and Environmental Medicine*, *56*(3), 298–303

Culpepper, P. D., & Thelen, K. (2020). Are We All Amazon Primed? Consumers and the Politics of Platform Power. *Comparative Political Studies*, *53*(2), 288–318. https://doi.org/10.1177/0010414019852687

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). *The business of platforms: Strategy in the age of digital competition, innovation, and power* (Vol. 320). New York: Harper Business.

Danaher, J. (2016). The Threat of Algocracy: Reality, Resistance and Accommodation. *Philosophy & Technology*, *29*.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining" gamification". In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments* (pp. 9-15).

Dubal, V. B. (2022). Economic security & the regulation of gig work in California: From AB5 to Proposition 22. *European Labour Law Journal*, *13*(1), 51-65.

Edwards, P. (1986). *Conflict at Work: A Materialist Analysis of Workplace Relations*. B. Blackwell.

Fayol, H. (1949). *General and Industrial Management*. Pitman and Sons, Ltd.

Flamholtz, E. G., Das, T. K., & Tsui, A. S. (1985). Toward an integrative framework of organizational control. *Accounting, Organizations and Society*, *10*(1), 35–50.

Friedman, A. (1977). Responsible Autonomy Versus Direct Control Over the Labour Process. *Capital & Class*, *1*(1), 43–57.

Fuller, L., & Smith, V. (1991). Consumers' Reports: Management by Customers in a Changing Economy. *Work, Employment and Society*, *5*(1), 1–16. https://doi.org/10.1177/095001709100500102

Gandini, A. (2019). Labour process theory and the gig economy. *Human Relations*, *72*(6), 1039–1056.

Glaser, B., & Strauss, A. (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Mill Valley, CA: Sociology Press.

Grohmann, R., Pereira, G., Guerra, A., Abilio, L. C., Moreschi, B., & Jurno, A. (2022). Platform scams: Brazilian workers' experiences of dishonest and uncertain algorithmic management. New Media & Society, 24(7), 1611-1631.

Gillespie, T. (2018). Regulation of and by platforms. In J. Burgess, T. Poell, & A. Marwick (Eds.), *The SAGE Handbook of Social Media* (pp. 254–278). SAGE Reference.

Goffman, E. (1963). Embarrassment and Social Organization. In N. J. Smelser & W. T. Smelser (Eds.), *Personality and social systems* (pp. 541–548). John Wiley & Sons, Inc.. https://doi.org/10.1037/11302-050

Goldberg, A., Srivastava, S. B., Manian, V. G., Monroe, W., & Potts, C. (2016). Fitting In or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness. *American Sociological Review*, *81*(6), 1190–1222.

Hannák, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., & Wilson, C. (2017). Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing* (pp. 1914-1933).

Hern, A. (2016). Uber and Lyft pull out of Austin after locals vote against self-regulation. The Guardian. https://www.theguardian.com/technology/2016/may/09/uber-lyft-austin-vote-against-self-regulation

Hill, J. D. (2020). *The Hustle Ethic and the Spirit of Platform Capitalism*. Stanford University.

Hochschild, A.R. (1983). *The managed heart: commercialization of human feeling*. University of California Press.

Hochschild, A. R. (2018). *Strangers in their own land: Anger and mourning on the American right*. The New Press.

Hu, W. (2022). *Inside the fight to pay delivery drivers 22 and Hour.* New York Times. Access at: https://www.nytimes.com/2022/12/08/nyregion/nyc-food-delivery-workers-wage-increase.html

Kamaswaren, V., Cameron, L., Dillahunt, T. (2018). Support for Social and Cultural Capital Development in Real-time Ridesharing Services. *Computer-Human Interactions. CHI 2018: ACM Conference on Human Factors in Computing Systems.*

Irani, L. (2013). The cultural work of microwork. New Media and Society. Volume 17, Issue 5. https://doi.org/10.1177/1461444813511926

Isaac, M. (2019). *Super pumped: The battle for Uber*. WW Norton & Company.

Isaac & Lohr (2017). ***Unroll.me Service Faces Backlash Over a Widespread Practice: Selling User Data. New York Times***

Isaac, M. (2017). Uber Ceo's Plays with Fire. New York Times.

Joyce, K., Smith-Doerr, L., Alegria, S., Bell, S., Cruz, T., Hoffman, S. G., ... & Shestakofsky, B. (2021). Toward a sociology of artificial intelligence: A call for research on inequalities and structural change. *Socius*, *7*, 2378023121999581.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366–410.

Kharpal, A. Uber Reportedly used secret software called "Hell' to track rival Lyft drivers. Published 13 April 2017, CNBC. Accessed: https://www.cnbc.com/2017/04/13/uber-lyft-hell-software-track-drivers.html

Korczynski, M. (2001). The contradictions of service work: call centre as customer-oriented bureaucracy. *Customer Service: empowerment and entrapment*, 79-101.

Locke, K. (2001). *Grounded Theory in Management Research.* Sage Publications.

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612.

Leidner R (1993) *Fast food, fast talk: Service work and the routinization of everyday life*. University of California Press.

Leonardi, P., & Treem, J. W. (2020). Behavioral Visibility: A New Paradigm for Organization Studies in the Age of Digitization, Digitalization, and Datafication. *Organization Studies*.

Levy, K. (2023). *Data driven: truckers, technology, and the new workplace surveillance*. Princeton University Press.

Macpherson, C. B. (1962). *The political theory of possessive individualism: Hobbes to Locke*. Oxford: Clarendon Press.

Maffie, M. (2022). The Perils of Laundering Control Through Customers: Conflict and Resistance in the Ridehail Industry. *Industrial & Labor Relations Review*.

Manriquez, M. (2019). Work-games in the gig-economy: a case study of Uber drivers in the city of Monterrey, Mexico. In *Work and labor in the Digital Age* (pp. 165-188). Emerald Publishing Limited.

Mayberry, K., Cameron, L. & Rahman, H. (2023) "Unhooking from the Matrix: The Rise of Algo-Activism" Routledge Handbook in the Future of Work. Bristol, UL.

McMillan Cottom, T. (2020). Where platform capitalism and racial capitalism meet: The sociology of race and racism in the digital society. *Sociology of Race and Ethnicity*, *6*(4), 441-449.

Möhlmann, M. (2021). Algorithmic nudges don't have to be unethical. *Harvard Business Review*, *22*.

Mollick, E. & Rothbard, N. (2014). Mandatory Fun: Consent, Gamification and the Impact of Games at Work. The Wharton School Research Paper Series. Available at SSRN: https://ssrn.com/abstract=2277103 or http://dx.doi.org/10.2139/ssrn.2277103

Noble, S. U. (2018). Algorithms of oppression. In *Algorithms of oppression*. New York university press.

O'neil, C. (2017). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

Occhiuto, N. (2017). Investing in independent contract work: The significance of schedule control for taxi drivers. *Work and Occupations*, *44*(3), 268-295.

Orlikowski, W. J. (2007). Sociomaterial Practices: Exploring Technology at Work. *Organization Studies*, *28*(9), 1435–1448. https://doi.org/10.1177/0170840607081138

Orlikowski, W. J., & Scott, S. V. (2015). The Algorithm and the Crowd: Considering the Materiality of Service Innovation. https://dspace.mit.edu/handle/1721.1/96870

Pratt, M. G., & Bonacio, S. (2016). Qualitative Research in I-O Psychology: Maps, Myths, and Moving Forward. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 9*(4), 6933-715.

Price, R. (28 March 2018). Personal interview.

Rahman, H. A. (2021). The Invisible Cage: Workers' Reactivity to Opaque Algorithmic Evaluations. *Administrative Science Quarterly*, *66*(4), 945-988.

Rahman, H., Karunkaran, A., & Cameron, L. (2023). Taming Platform Power: An Integrative Framework for How to Hold Multi-Sided Platforms Accountable. *Academy of Management Annals.*

Rahman, H. A., Weiss, T., & Karunakaran, A. (2023). The experimental hand: How platform-based experimentation reconfigures worker autonomy. *Academy of Management Journal*,

Ravenelle, A.J. (2017) Sharing economy workers: selling, not sharing, *Cambridge Journal of Regions, Economy and Society*, Volume 10, Issue 2, Pages 281–295, https://doi.org/10.1093/cjres/rsw043

Ravenelle, A.J. (2018). The New Entepreneur: Worker Experiences in the Sharing Economy. Available at SSRN: https://ssrn.com/abstract=3187539

Ravenelle, A. J. (2019). *Hustle and Gig: Struggling and Surviving in the Sharing Economy*. University of California Press.
Reid 2015

Ravenelle, A. J., Janko, E., & Kowalski, K. C. (2022). Good jobs, scam jobs: Detecting, normalizing, and internalizing online job scams during the COVID-19 pandemic. *New media & Society*, *24*(7), 1591-1610.

Rogoway, M. (2020). *Major Tech Company Using Facial Recognition to ID Workers*. GovTech. https://www.govtech.com/public-safety/Major-Tech-Company-Using-Facial-Recognition-to-ID-Workers.html

Rosenblat, A. (2018). *Uberland: How Algorithms are Rewriting the Rules of Work*. University of California Press.

Rosenblat, A. & Stark, L. (2016). Uber's Drivers: Information Asymmetries and Control in Dynamic Work. *International Journal of Communication*, *10*(27). https://doi.org/10.2139/ssrn.2686227

Rosenthal, P. (2004). Management Control as an Employee Resource: The Case of Front-line Service Workers. *Journal of Management Studies, 41*(4), 601–622.

Rynes, S. & Bartunek, J. (2015). It Just Keeps Getting More Interesting. In Elsbach, K. D. & Kramer, R. (eds.), *Handbook of Qualitative Organizational Research*. Routledge.

Scheiber, N. (2017). How Uber Uses Psychological Tricks to Push Its Drivers' Buttons. *The New York Times*. https://www.nytimes.com/interactive/2017/04/02/technology/Uber-drivers-psychological-tricks.html

Schor, J. (2021). *After the gig: How the sharing economy got hijacked and how to win it back*. University of California Press.

Shapiro, A. (2018). Between autonomy and control: Strategies of arbitrage in the "on-demand" economy. *New Media & Society*, *20*(8), 2954–2971.

Shestakofsky, B. (2017). "Working Algorithms: Software Automation and the Future of Work." *Work and Occupations* 44(4):376-423.

Shevchuk, A., Strebkov, D., & Davis, S. N. (2019). The Autonomy Paradox: How Night Work Undermines Subjective Well-Being of Internet-Based Freelancers. *ILR Review*, *72*(1), 75–100.

Spreitzer, G. M., Cameron, L., & Garrett, L. (2017). Alternative Work Arrangements: Two Images of the New World of Work. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*(1), 473–499.

Streeter, T. (2015). Steve jobs, romantic individualism, and the desire for good capitalism. *International Journal of Communication, 9,* 3106–3124.
Thelen, K. (2018). Regulating Uber: The politics of the platform economy in Europe and the United States. Perspectives on Politics, 16(4), 938-953.

Thorp, A. A., Healy, G. N., Winkler, E., Clark, B. K., Gardiner, P. A., Owen, N., & Dunstan, D. W. (2012). Prolonged sedentary time and physical activity in workplace and non-work contexts: A cross-sectional study of office, customer service and call centre employees. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 128.

Tolentino, J. (2017). The gig economy celebrates working yourself to death. *The New yorker*, *22*

Vallas, S., & Schor, J. B. (2020). What Do Platforms Do? Understanding the Gig Economy. *Annual Review of Sociology*, *46*(1).

Van Maanen, J. (1991). The smile factory: work at Disneyland. *Organizational Culture,* Sage.

Van Maanen, J., & Barley, S. (1984). Occupational Communities: Culture and control in organizations. *Research in Organizational Behavior*, *6*, 287–365.

Wang, X. & Reger, R. K. (2017). Rolling the Dice: What Methodological Choices Maximize Chances for Publication in Premier Strategic Management Journals? In Galavan, R., Sund, K. and Hodgkinson, G. (eds.), *Methodological Challenges and Advances in Managerial and Organizational Cognition* (*New Horizons in Managerial and Organizational Cognition, Vol. 2*). Emerald Publishing.

Watkins, E. A. (2021). *The Polysemia of Recognition: Facial Recognition in Algorithmic Management*. [Doctoral dissertation.] Columbia University.

Watkins, E. A. (2023). Face Work: A Human-Centered Investigation into Facial Verification in Gig Work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1-24.

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society*, *33*(1), 56–75.

Wood, A. J., & Lehdonvirta, V. (2021). Antagonism beyond employment: how the 'subordinated agency'of labour platforms generates conflict in the remote gig economy. *Socio-Economic Review*, *19*(4), 1369-1396.

Wong, J. (2017). Greyball: How Uber Used Secret Software to Dodge the Law. *The Guardian*. Accessed at https://www.theguardian.com/technology/2017/mar/03/uber-secret-program-greyball-resignation-ed-baker

Youshaei, J. (2015, February 4). The Uberpreneur: How an Uber drivers makes $252,000 a year. *Forbes*. Retrieved from https://www.forbes.com/sites/jonyoushaei/2015/02/04/the-uberpreneur-how-an-uber-driver-makes-252000-a-year/#650040004e8e.

Zuboff, S. (2019). *The Age of Surveillance capitalism: The Fight for a Human Future at the New Frontier of Power*. Profile Books.

Appendix A

Prior Expert Work

1. 2021. Gachie v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Houston, TX; Deposition and Arbitration
2. 2021. Omey v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Houston, TX; Deposition and Arbitration
3. 2021. Chitambira v. Uber Technologies, Inc.; Kherkher Garcia; plaintiff; Dallas, TX; Arbitration
4. 2022. Barysas v. Uber Technologies, Inc; plaintiff; Houston, TX; Deposition and Arbitration
5. 2021, 2019. Testimony provided for hearing held by the Pennsylvania State Senate Democratic Policy Committee

EXHIBIT 3

Clerk of the Superior Court
*** Electronically Filed ***
03/15/2023 8:00 AM

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2018-005515 03/14/2023

HONORABLE JOAN M. SINCLAIR

CLERK OF THE COURT
S. Motzer
Deputy

GABRIEL JAMES COSLETT NATHANIEL B PRESTON

v.

YURIC ALEXANDER HANNART, et al. ADAM B CAMPBELL

BRIAN DEL GATTO
JENNIFER R REBHOLZ
JUDGE SINCLAIR

UNDER ADVISEMENT RULING

Defendants Uber Technologies, Inc., and Rasier, LLC (a subsidiary of Uber) (jointly "Uber") filed a Motion for Summary Judgment on October 7, 2022. The matter has been fully briefed. Oral argument was held on February 24, 2023, and the matter was taken under advisement. The Court now rules.

Under Rule 56(a) of the Arizona Rules of Civil Procedure "[t]he court shall grant summary judgment if the moving party shows that there is no genuine dispute as to any material fact and the moving party is entitled to judgment as a matter of law." The moving party bears the burden of demonstrating both absence of any factual conflict and right to judgment. *Nat'l Bank of Ariz. v. Thurston*, 218 Ariz. 112, 114-115, ¶ 12 (App. 2008).

Uber asserts that it is entitled to summary judgment because driver Hannart is an independent contractor. Motion, p. 2. Plaintiff Coslett ("Coslett") claims that Hannart is an "employee, agent, and/or representative" of Uber (Complaint, ¶¶ 7-8) and therefore, both companies are "vicariously and jointly and severally liable" for the vehicular accident. Complaint ¶¶ 24, 30. The Court agrees with Uber for the reasons noted below.

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2018-005515 03/14/2023

A.R.S. 1603(E)(2)(a)-(b) defines a qualified marketplace platform as an entity that both:

> (a) Operates a digital website or digital smartphone application that facilitates the provision of services by qualified marketplace contractors to individuals or entities seeking such services.
>
> (b) Accepts service requests from the public only through its digital website or digital smartphone application, and does not accept service requests by telephone, by facsimile or in person at physical retail locations.

This is what Uber does. Uber is a qualified marketplace platform. Hannart, therefore, is a qualified marketplace contractor. By statute, "[a] qualified marketplace contractor shall be treated as an independent contractor for all purposes under state and local laws, regulations and ordinances... ." A.R.S. §23-1603.

The Technology Services Agreement ("TSA") between Uber and Hannart identifies Hannart as an independent contractor, although the language of the contract is not controlling here. Motion, Exhibit E. Even under common law, the distinction between an independent contractor and an employee "rests on the extent of control the employer may exercise over the details of the work." *Munoz v. Indus. Comm'n of Arizona*, 234 Ariz. 145, 150, ⁋15 (App. 2014) (internal quotations and citations omitted).

Many of Coslett's asserted proofs of Uber's control over Hannart are mandated by the statutes. Response, pp. 11-12. A.R.S. § 28-9555 requires the potential driver for a digital network company to submit an application to the company, and the company must conduct a criminal background check, obtain a driving history, and ensure the vehicle meets safety standards through periodic inspection. Despite all of these requirements, these drivers are still considered independent contractors under A.R.S. § 23-1603(A).

The fact that "Uber requires its drivers to fill out incident reports in the event of an accident," (Response, p. 12) is not significant, because transportation network companies like Uber are required to provide insurance coverage under A.R.S. § 28-4038. Similarly, the Uber Community Guidelines (Response, Exhibit 26) are basic guidelines and rules for both riders and drivers, and also do not show control by Uber over Hannart.

Hannart signed the TSA with Rasier in 2016 and accepted the Arizona addendum 2017 which allowed him to use the Driver App. Motion SOF, § 5, 9. His pay was dependent on the riders he picked up as opposed to any salary or hourly wage received. Exhibit A-1 (TSA, §§ 4.1—4.5). He had complete control over his work hours and days as well as which riders to accept or decline. Motion SOF, ¶¶21, 26, 28. Hannart was free to pursue employment with other driving services,

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2018-005515 03/14/2023

and he apparently did. Motion SOF, ¶ 18; Reply SOF, ¶ 19; Defendants' Controverting SOF Exhibit 1 ("Deposition of Yuric Hannart"), p. 32. He used his own vehicle and received a 1099 tax form. Motion SOF, ⁋⁋ 22, 30.

Uber does not independently evaluate driver performance, like conducting a supervisor ride along, but instead bases any performance feedback on customer ratings. Motion SOF, § 31. There is no boss or supervisor from Uber to whom Hannart reports his results. Defendants' Controverting SOF Exhibit 1 ("Deposition of Yuric Hannart"), p. 31, 38. Either contracting party was free to terminate the TSA without cause at any time. Exhibit A-1 (TSA § 12.2). Uber does not set a quota for the number of rides a driver must provide within a certain period. All of these facts demonstrate that Hannart was an independent contractor, not an employee.

Because Hannart was an independent contractor, Uber cannot be vicariously liable for Hannart's actions. In addition to these arguments, Coslett also argues that Uber has a non-delegable duty, there was a joint venture between Uber and Hannart, and there is independent negligence based on Uber's business model. These latter arguments do not appear in the Complaint and so the Court could summarily dismiss them. Nevertheless, those arguments also do not support Coslett's claims.

The TSA clearly states that Uber and Hannart are not establishing a joint venture. Defendants' Exhibit A, Section 13.1. A joint venture requires "(1) a contract; (2) a common purpose; (3) a community of interest: (4) an equal right to control; and (5) participation in the profits and losses." *Tanner Companies v. Superior Ct.,* 144 Ariz. 141, 143 (1985) (citation omitted). In this situation, Uber and Hannart do not share an equal right to control and there is no participation in the profits and losses. Uber does not control the time or manner of how Hannart provides transportation for riders. Hannart has no control over how Uber manages its business. Hannart is paid based on the rides he provides; he has no share in the overall profits or losses of Uber. This is not a joint venture.

Nor is driving an inherently dangerous activity such that it creates a non-delegable duty in Uber. Non-delegable duties are imposed by "statute, by contract, by franchise or charter, or by the common law." *Santorii v. MartinezRusso, LLC,*240 Ariz. 454, 458, ⁋14 (App. 2016) (citation omitted). An activity is inherently dangerous "(1) if the risk cannot be eliminated through the exercise of reasonable care; and (2) the risk is to the person, land or chattels of another." *Pride of San Juan, Inc. v. Pratt,* 221 Ariz. 337, 340, ⁋11 (App. 2009) (internal quotations and citations omitted). Coslett has provided no evidence to support the claim that driving is an inherently dangerous activity. Additionally, Coslett has also provided no evidence to support the claim that Uber's business model presents a special danger to motorists.

Therefore,

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2018-005515 03/14/2023

IT IS ORDERED granting Uber's motion for summary judgment.

IT IS FURTHER ORDERED that Defendants shall submit a proposed order of judgment to the Court by April 3, 2023.

EXHIBIT 4

Clerk of the Superior Court
*** Electronically Filed ***
08/23/2022 8:00 AM

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2019-000428 08/21/2022

HONORABLE SCOTT BLANEY

CLERK OF THE COURT
P. McKinley
Deputy

JORDAN JAMES KLOSA KELLEN W BRADLEY

v.

MARTIN BARRY GOLDMAN, et al. ADAM B CAMPBELL

DANIEL R MOWREY
CHARLES B WILLIAMSON
JENNIFER R REBHOLZ
BRIAN DEL GATTO
TAYLOR H ALLIN
JUDGE BLANEY

UNDER ADVISEMENT RULING

The Court has reviewed and considered Defendants Uber Technologies, Inc. and Rasier, LLC's *Motion for Summary Judgment*, Plaintiff's *Response* thereto, Defendants' *Reply* in support of their *Motion*, Defendant Martin Goldman's *Joinder to Uber Technologies, Inc. and Rasier, LLC's Motion for Summary Judgment*, Defendants' *Statement of Facts in Support of Their Motion for Summary Judgment*, Defendants' *Notice of Errata*, Plaintiff's *Response to Defendants' Statement of Facts and Plaintiff's Statement of Additional Facts*, and the arguments received at the August 18, 2022 oral argument.

Summary judgment is appropriate if no genuine issue of material fact exists and the moving party is entitled to judgment as a matter of law. *See* Rule 56(a), *Arizona Rules of Civil Procedure*; *Orme School v. Reeves*, 166 Ariz. 301, 305, 802 P.2d 1000, 1004 (1990); *Hourani v. Benson Hosp.*, 211 Ariz. 427, 432, 122 P.3d 6, 11 (App. 2005).

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2019-000428 08/21/2022

THE COURT FINDS AS FOLLOWS:

1. Uber is a global technology company that uses technology to develop and maintain digital multi-sided platforms. These multi-sided platforms are digital marketplaces where providers or sellers of a good or service can connect with consumers of that good or service. Uber's platforms provide users (both the sellers and buyers) with various services, including matching and payment processing.

2. Uber has created several mobile applications available via smartphone or tablet that allow Riders, Restaurants, Drivers, and delivery people to access its various platforms. One of Uber's platforms is the Rides platform. Riders download the rider version of the Uber App ("Rider App") and Drivers download the Driver version of the Uber App ("Driver App"); together, the Apps allow users to access the platform that facilitates the connection of individuals in need of a ride ("Riders") with individuals willing to provide transportation services ("Drivers").

3. Rasier is an Uber subsidiary and a transportation network company as defined by A.R.S. § 28-9551(3), which licenses the use of the Driver App to drivers.

4. Uber and Rasier are both "Qualified Marketplace Platforms" as defined by A.R.S. § 23-1603(E)(2), because each is an "organization … that both: (a) Operates a digital website or digital smartphone application that facilitates the provision of services by qualified marketplace contractors to individuals or entities seeking such services; and (b) Accepts service requests from the public only through its digital website or digital smartphone application…."

5. Defendant Martin Goldman earns an income by responding through Uber's Driver App to requests for transportation services from passengers seeking such services through Uber's Rider App. Thus, Uber's Apps connect the two parties (Driver and Rider) that are seeking to provide and to utilize, respectively, transportation services. On the date in question, Defendant Goldman was transporting one or more passengers when his vehicle collided with Plaintiff's motorcycle.

6. Defendant Goldman is a "Qualified Marketplace Contractor" because he is a "person … that enter[ed] into an agreement with a qualified marketplace platform (Uber and Rasier) to use the qualified marketplace platform's digital platform to provide services to third-party individuals … seeking those services." A.R.S. § 23-1603(E)(1).

SUPERIOR COURT OF ARIZONA
MARICOPA COUNTY

CV 2019-000428 08/21/2022

7. Pursuant to A.R.S. § 23-1603(A), Defendant Goldman's relationship with Defendants Uber and Rasier was that of an independent contractor "for all purposes under state and local laws, regulations and ordinances…." *Id.* Defendants' relationship was governed by a written contract (*see* Finding #6, above) that satisfied each of the individual criteria listed in A.R.S. § 23-1603(A)(3)(a)-(g). Defendant Goldman was therefore an independent contractor.

8. It is well-established in Arizona that an employer is generally not liable for the negligence of an independent contractor. *Wiggs v. City of Phoenix*, 198 Ariz. 367, 369, 10 P.3d 625, 627 (2000); *Santorii v. MartinezRusso, L.L.C.*, 240 Ariz. 454, 459, 381 P.3d 248, 253 (App. 2016).

9. Plaintiff argues that even if Defendant Goldman is an independent contractor, Defendants Uber and Rasier may still be liable because Mr. Goldman is their agent. An independent contractor, although not a servant, can still be an agent of the principal. *Wiggs*, 198 Ariz. at 628, 10 P.3d at 370. In such cases, the principal instructs the agent on what to do, but not how to do it. *Id.*; *Santorii*, 240 Ariz. at 459, 381 P.3d at 253. The focus of the analysis is on the amount of control that the principal exercises. *Santorii*, 240 Ariz. at 459, 381 P.3d at 253. "The right to control is not established when the entity cannot control the worker's time or the method and the means of how the work is completed." *Id.* The existence of agency is a question of law when there is "no competent evidence legally sufficient to prove it" in the record or "the material facts from which it is to be inferred are undisputed and only one conclusion can be drawn therefrom." *Schenks v. Earnhardt Ford Sales Company*, 9 Ariz.App. 555, 557, 454 P.2d 873, 875 (App. 1969).

10. Defendants Uber and/or Rasier did not materially control Defendant Goldman's time or the method and the means of how he completed his work. For example, Goldman was free to choose his own hours and days for driving. Goldman could market his services and perform the same transportation services for Riders through the app of a competitor to Uber/Rasier. Goldman was free to accept or decline requests for transportation through the Driver App. Goldman used his own vehicle to provide the service to Riders. And Goldman could determine the route and which navigation app he would use when providing transportation services. Defendants Uber and Rasier did not require Goldman to wear a uniform when using the Driver App.

11. Plaintiff's arguments in support of a finding of agency are not compelling. As just some examples, Plaintiff argues, *inter alia*, that "Goldman was driving an Uber certified vehicle." Response at pg. 3. Plaintiff further argues that Goldman "was qualified by Uber to access Uber's platform (APP)…." *Id.* Plaintiff also points to the

Uber logo displayed on Goldman's windshield when he is providing transportation services. *Id.* But these requirements cited by Plaintiff were actually required by Arizona law, not Uber or Rasier as principals or employers. *See* A.R.S. §§ 28-9555(A) and 28-9552(D); *see also* A.R.S. § 23-1602 (precluding "any supervision or control exercised by an employing unit to comply with…" statutes, rules, codes, licensing requirements, or professional standards from being considered for purposes of determining independent contractor versus employment status).

12. There is insufficient competent evidence in the record to establish a genuine factual dispute regarding Uber's or Rasier's control of Defendant Goldman's time and/or the method and means of how he provided transportation services. *Santorii*, 240 Ariz. at 459, 381 P.3d at 253. Uber and Raiser did not control Defendant Goldman's time or the method and means of how he provided services such that liability for Defendant Goldman's alleged negligence may be imputed to Uber or Raiser. *See Wiggs*, 198 Ariz. at 369, 10 P.3d at 627 (employer generally not liable for the negligence of an independent contractor); *Santorii*, 240 Ariz. at 459, 381 P.3d at 253 (same).

13. There is also insufficient competent evidence in the record to support Plaintiff's negligence claims against Uber and/or Rasier. There was no competent evidence received establishing – or even suggesting – that Uber and/or Rasier "antecedently had reason to believe that an undue risk of harm would exist" if Defendant Goldman were permitted to use the Driver App. *See Kassman v. Busfield Enterprises, Inc.*, 131 Ariz. 163, 166, 639 P.2d 353, 356 (App. Div.2 1981) (principal is not liable simply because agent is incompetent or careless; liability only arises if principal had reason to anticipate undue risk of harm) (citing Restatement (Second) of Agency, § 213). There is no competent evidence in the record that Defendant Goldman's statutorily-required background and driver's licenses checks identified any such risks. And the Court notes that no special training was required for Defendant Goldman to provide his driving services. *Id.*

14. No genuine issues of material fact exists as to the disputed claims and Defendants Uber and Rasier are entitled to judgment as a matter of law.

IT IS THEREFORE ORDERED granting Defendants' *Motion for Summary Judgment* and dismissing all claims asserted against Defendants Uber Technologies, Inc. and Rasier, L.L.C.

IT IS FURTHER ORDERED Defendants shall lodge a proposed form of Judgment and file their attorney's fee application and affidavit in support thereof, and file, if appropriate, their statement of costs, within **20 days** of the filing date of this Minute Entry; Plaintiff shall file any

objections thereto within **20 days** thereafter; and Defendants shall file their replies within **10 days** thereafter.

IT IS FURTHER ORDERED the Judgment shall contain Rule 54(b) language as no further matters remain pending as to Defendants Uber Technologies, Inc. and Rasier, L.L.C. and there is no just reason for delay.